EXHIBIT D

IN THE
UNITED STATES DISTRICT COURT
FOR THE EASTERN DISTRICT OF NORTH CAROLINA
EASTERN DIVISION

RODNEY D. PIERCE; *et al.*, Plaintiffs, v. **THE NORTH CAROLINA STATE BOARD OF ELECTIONS; *et al.***,, Defendants,	Case No. 4:23-cv-193-D

EXPERT REPORT OF SEAN P. TRENDE, Ph.D.

1 Expert Qualifications

1.1 Career

I serve as Senior Elections Analyst for Real Clear Politics. I joined Real Clear Politics in January of 2009 and assumed a fulltime position in March of 2010. Real Clear Politics is a company of approximately 50 employees, with its main offices in Washington D.C. It produces one of the most heavily trafficked political websites in the world, which serves as a one-stop shop for political analysis from all sides of the political spectrum and is recognized as a pioneer in the field of poll aggregation. Real Clear Politics produces original content, including both data analysis and traditional reporting.

My main responsibilities with Real Clear Politics consist of tracking, analyzing, and writing about elections. I collaborate in rating the competitiveness of Presidential, Senate, House, and gubernatorial races. As a part of carrying out these responsibilities, I have studied and written extensively about demographic trends in the country, exit poll data at the state and federal level, public opinion polling, and voter turnout and voting behavior. In particular, understanding the way that districts are drawn and how geography and demographics interact is crucial to predicting United States House of Representatives races, so much of my time is dedicated to that task.

I am currently a Visiting Scholar at the American Enterprise Institute, where my publications focus on the demographic and coalitional aspects of American Politics.

I am also a Lecturer at The Ohio State University. My courseload is detailed below.

1.2 Publications and Speaking Engagements

I am the author of the 2012 book The Lost Majority: Why the Future of Government is up For Grabs and Who Will Take It. In this book, I explore realignment theory. It argues that realignments are a poor concept that should be abandoned. As part of this analysis, I conducted a thorough analysis of demographic and political trends beginning

in the 1920s and continuing through modern times, noting the fluidity and fragility of the coalitions built by the major political parties and their candidates.

I also co-authored the 2014 Almanac of American Politics. The Almanac is considered the foundational text for understanding congressional districts and the representatives of those districts, as well as the dynamics in play behind the elections. My focus was researching the history of and writing descriptions for many of the 2012 districts, including tracing the history of how and why they were drawn the way that they were drawn. Because the 2014 Almanac covers the 2012 elections, analyzing how redistricting was done was crucial to my work. I have also authored a chapter in Dr. Larry Sabato's post-election compendium after every election dating back to 2012.

I have spoken on these subjects before audiences from across the political spectrum, including at the Heritage Foundation, the American Enterprise Institute, the CATO Institute, the Bipartisan Policy Center, and the Brookings Institution. In 2012, I was invited to Brussels to speak about American elections to the European External Action Service, which is the European Union's diplomatic corps. I was selected by the United States Embassy in Sweden to discuss the 2016 elections to a series of audiences there and was selected by the United States Embassy in Spain to fulfill a similar mission in 2018. I was invited to present by the United States Embassy in Italy, but was unable to do so because of my teaching schedule.

1.3 Education

I received my Ph.D. in political science at The Ohio State University in 2023. I passed comprehensive examinations in both Methodology and American Politics. The first chapter of my dissertation involves voting patterns on the Supreme Court from 1900 to 1945; the second chapter involves the application of integrated nested LaPlace approximations to enable the incorporation of spatial statistical analysis in the study of United States elections. The third chapter of the dissertation involves the use of communities of interest in redistricting simulations. In pursuit of this degree, I also earned a Mas-

ter's Degree in Applied Statistics. My coursework for my Ph.D. and M.A.S. included, among other things, classes on G.I.S. systems, spatial statistics, issues in contemporary redistricting, machine learning, non-parametric hypothesis tests and probability theory. I also earned a B.A. from Yale University in history and political science in 1995, a Juris Doctor from Duke University in 2001, and a Master's Degree in political science from Duke University in 2001.

In the winter of 2018, I taught American Politics and the Mass Media at Ohio Wesleyan University. I taught Introduction to American Politics at The Ohio State University for three semesters from Fall of 2018 to Fall of 2019, and again in Fall of 2021. In the Springs of 2020, 2021, 2022 and 2023, I taught Political Participation and Voting Behavior at The Ohio State University. This course spent several weeks covering all facets of redistricting: how maps are drawn, debates over what constitutes a fair map, measures of redistricting quality, and similar topics. It also covers the Voting Rights Act and racial gerrymandering claims. I also taught survey methodology in Fall of 2022 and Spring of 2024.

1.4 Prior Engagements as an Expert

A full copy of all cases in which I have testified or been deposed is included on my C.V., attached as Exhibit 1. In 2021, I served as one of two special masters appointed by the Supreme Court of Virginia to redraw the districts that will elect the Commonwealth's representatives to the House of Delegates, state Senate, and U.S. Congress in the following decade. The Supreme Court of Virginia accepted those maps, which were praised by observers from across the political spectrum. [1]

In 2019, I was appointed as the court's expert by the Supreme Court of Belize.

[1] *See, e.g.*, *New Voting Maps, and a New Day, for Virginia*, The Washington Post (Jan. 2, 2022), available at `https://www.washingtonpost.com/opinions/2022/01/02/virginia-redistricting-voting-maps-gerrymander`; Henry Olsen, *Maryland Shows How to do Redistricting Wrong. Virginia Shows How to Do it Right*, The Washington Post (Dec. 9, 2021), available at `https://www.washingtonpost.com/opinions/2021/12/09/maryland-virginia-redistricting`; Richard Pildes, *Has VA Created a New Model for a Reasonably Non-Partisan Redistricting Process*, Election Law Blog (Dec. 9, 2021), available at `https://electionlawblog.org/?p=126216`.

In that case I was asked to identify international standards of democracy as they relate to malapportionment claims, to determine whether Belize's electoral divisions (similar to our congressional districts) conformed with those standards, and to draw alternative maps that would remedy any existing malapportionment.

I served as a Voting Rights Act expert to counsel for the Arizona Independent Redistricting Commission in 2021 and 2022.

2 Scope of Engagement

I have been retained by Nelson Mullins, LLP on behalf of their clients, Defendants in the above-titled action, Timothy K. Moore, North Carolina Speaker of the House and Philip E. Berger, President Pro Tempore of the North Carolina Senate, to evaluate the 2024 North Carolina Senate Map (hereinafter "Enacted Map"). I have been retained and am being compensated at a rate of $500 per hour, to provide my expert analysis to evaluate the claims presented by Dr. Jonathan Mattingly and Mr. Blakeman B. Esselstyn. In particular, I evaluate the claims of Dr. Mattingly in his Expert Report of Dr. Jonathan Mattingly ("Mattingly Report") and by Mr. Esselstyn in his Expert Report of Blakeman B. Esselstyn ("Esselstyn Report"). All opinions and findings are given to a reasonable degree of scientific certainty typical of my field.

3 Summary of Opinions

Dr. Mattingly and Mr. Esselstyn perform discrete, yet interrelated functions. Mr. Esselstyn's report offers four illustrative districts that purport to show that there exists a grouping of Black residents of North Carolina suffiently compact and numerous to constitute a majority of the population in a reasonably configured district. Dr. Mattingly then demonstrates the *Stephenson* groupings that would surround these districts. My major conclusions are as follows.

- Mr. Esselstyn's maps all change the existing *Stephenson* groupings;
- Mr. Esselstyn's District B-1 is not majority Black CVAP using the most up-to-date census data;
- Mr. Esselstyn cannot say with a reasonable degree of scientific certainty that districts B-1 and D-1 have majority Black CVAPs;
- There is no *Gingles I* district in the Edge-Pittcombe cluster;
- Dr. Mattingly's *Stephenson* groupings for Map A depend upon the freezing of Pitt-Edgecombe.

4 Data

In addition to the sources mentioned in my report and in my accompanying code, data were downloaded from the Redistricting Data Hub, a source for redistricting data widely used by social scientists and the broader redistricting community. I also relied upon the opposing experts' reports and their accompanying code, and documents referenced in that code and those reports.

5 Analysis

5.1 Background on the American Community Survey

Before discussing the specific issues in this matter, I first provide an overview of the American Community Survey ("ACS"), as well as a brief explanation of statistical inference.

5.1.1 Census geographies

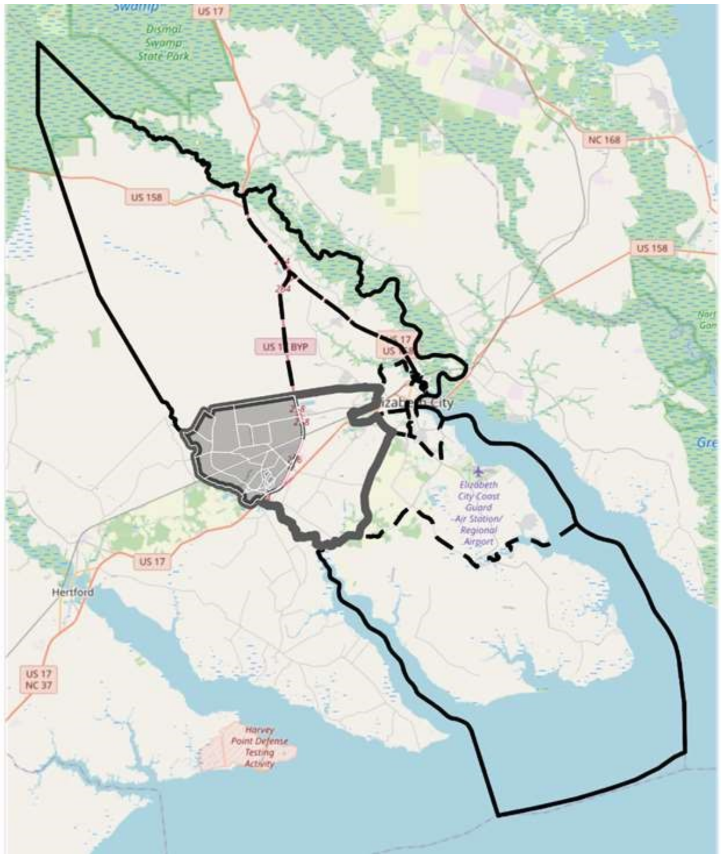
The US Census Bureau reports data at multiple levels of data collection. The largest grouping is obviously at the national level, but the data are further broken down

at the state level, and then to the county level.

Counties are then further broken down into census tracts. North Carolina has 1,776 census tracts. Following the 2020 decennial census, the average population of a tract in North Carolina was 5,878 residents; the largest tract contained 34,130 residents, while the smallest contained 0. Census tracts are divided into block groups; there are 4,967 in North Carolina. Following the 2020 census, the average block group in North Carolina contained 2,102 residents. The largest had 13,967 residents, while the smallest again contained zero. Finally, block groups are divided into census blocks, of which there are 236,638 in North Carolina. On average, they contain 44 residents, although the largest contains 3,419.

To help illustrate this better, the following map is of Pasquotank County in North Carolina. Pasquotank County has 989 blocks total, 32 block groups, and 10 census tracts. The dashed lines on the map illustrate those ten census tracts into which that county is divided. Tract 9606 is outlined in a dark grey border. Tract 9606 is divided into two block groups. Block Group 1 is shaded grey, while Block Group 2 is still transparent. Block Group 1 has 40 census blocks, which are outlined in white.

Figure 1: Census levels in Pasquotank County, North Carolina



5.1.2 ACS Overview

The ACS is designed to "provide communities with reliable and timely social, economic, housing, and demographic data every year." United States Census Bureau, *Understanding and Using American Community Survey Data: What all Data Users Need to Know* 1, available at `https://www.census.gov/content/dam/Census/library/publications/2020/acs/acs_general_handbook_2020_ch01.pdf` (hereinafter "ACS Handbook"). It samples about 3.5 million individuals nationwide annually. *Id.* Unlike the decennial census, these numbers are not collected at a single point in time. *Id.* Rather, they are collected over the course of the year.

The census publishes the results of the ACS on an annual basis, called the "one-

year estimates," but it only does so for geographies that contain more than 65,000 individuals. *Id.* Data are made available for smaller geographies in what are called five-year estimates, because they group together responses across a 60-month time period. *Id.* at 1. In other words, the interviews for the 2020 five-year estimates are *not* mostly conducted in 2020. Rather, they are spread across 2016, 2017, 2018, 2019, and 2020 and they "do not describe any specific day, month, or year within that time period." *Id.* at 13. Put differently, as of today, the 2020 estimates contain data that are close to a decade old; the average data was likely collected sometime in 2018. Data at the block group level is only available in the 5-year estimates. Unlike the decennial census, which records precise information down to the census block level, the block group is the smallest level to which ACS data are reported. *Id.* at 12.

The census also produces a special tabulation to the ACS, which contains the "Citizen Voting Age Population by Race and Ethnicity" data. Because the United States Census Bureau was not permitted to include a question on citizenship on the decennial census, see *Department of Commerce v. New York*, 588 U.S. ___ (2019), we do not have the exact numbers reported by the United States Census Bureau upon which to rely. Instead, we must rely upon the results drawn from a sample. These estimates are broken down as far as the block group level and describe the estimated number of residents of each geographic region who are citizens. The estimates are further broken down by race and ethnicity. This special tabulation is what the CVAP estimates used in the various expert reports here are based upon.

5.1.3 The ACS is a sample, and there are consequences to that

If you have ever heard a political poll reported, you have probably heard that the result has Candidate A leading Candidate B in a poll "with an error margin of +/- 3.5%" or some such. You've also probably heard a race called "within the error margin," as shorthand for "we can't really say whether Candidate A is really ahead of Candidate B." What this means in more precise statistical terms is explained below, but for our purposes

here, it is enough to say that (a) because the ACS is based upon a sample, it also comes with error margins and (b) those error margins mean that the topline numbers, or "point estimates," have real uncertainty surrounding them that can complicate comparisons to other numbers. The Census Bureau explains:

> The data in American Community Survey (ACS) products are estimates of the actual figures that would have been obtained if the entire population—rather than the chosen ACS sample—had been interviewed using the same methodology. All estimates produced from sample surveys have uncertainty associated with them as a result of being based on a sample of the population rather than the full population. This uncertainty—called sampling error—means that *estimates derived from the ACS will likely differ from the values that would have been obtained if the entire population had been included in the survey*, as well as from values that would have been obtained had a different set of sample units been selected for the survey.

ACS Handbook at 53 (emphasis added).

Sampling error is something that is inherent in polling. It grows out of the math surrounding the uncertainty inherent in talking with a sample of the overall population (as opposed to talking to everyone, which is a census rather than a sample). Put differently, if the world's greatest pollster conducts a poll of 475 people showing a presidential job approval of 50%, it will have an error margin of +/- 4.5%. If the world's worst pollster conducts a poll of 475 people showing a presidential job approval of 50%, it will also have an error margin of roughly 4.5%.[2] In general, the larger the sample, the smaller the level of sampling error.

Unlike social science (and public polling), which typically reports results with a 95% degree of confidence, the ACS reports 90% confidence intervals. A 90% confidence interval means that we expect the true population value of a given estimate to fall into a

[2]Note that there are other types of error associated with polling, such as errors that come from not sampling a representative sample of the population or groups of persons refusing to take a poll, but those are in addition to sampling error, not a part of sampling error.

reported confidence interval nine times out of ten. *Id.* So, for example, if a poll estimates Joe Biden's job approval at 45%, with an error margin at 90% confidence of +/- 4%, the 90% confidence interval would be 41% to 49%. In nine polls out of ten, that confidence interval would have the true value in it somewhere. Critically, we don't know where in the confidence interval the true population value falls (if indeed it does) or if this is the one time out of ten that the true population value falls outside of the confidence interval. We just know that as we keep taking polls, our population value will fall within the confidence interval one time out of ten.

The 90% confidence intervals reported by the census can easily be transformed into more traditional 95% confidence intervals by determining the standard error through a process described on page 55 of the ACS handbook, and then multiplying by the appropriate "z-statistic." For a 95% confidence interval, the z-statistic would be 1.96.

5.1.4 How a hypothesis test works

Confidence intervals exist whether or not they are acknowledged. The importance of acknowledging them, however, can depend on the application. For example, if I casually mention in writing that President Biden's job approval in a poll is 43% to suggest that he is unpopular, and it doesn't really matter if it is 44% or 42% in the general population, I might not mention the error margins. Of course, people also often simply forget about them. If, however, you are attempting a direct comparison to a specific value—say, Joe Biden's job approval is under 50%–it's important to take the uncertainty inherent in sampling into account. The confidence intervals likewise don't disappear just because a researcher forgets them.

The ACS is emphatic about this. On the first page of the ACS Handbook, it sets aside a special box that reads "TIP: In general, data users should be careful in drawing conclusions about small differences between two ACS estimates because they may not be statistically different." *ACS Handbook*, at 1. On page 17, it clarifies that "ACS data users interested in making comparisons also need to pay attention to sampling error because

differences between estimates may, or may not, be statistically significant." *Id.* at 17. This is to show "whether the observed difference between estimates likely represents a true difference that exists within the full population (is statistically significant) or instead has occurred by chance because of sampling (is not statistically significant)." *Id.* at 55.

We can do this via confidence intervals or a hypothesis test, which are ultimately different forms of the same exercise. With a confidence interval, the idea is simple: If the desired comparator falls within the confidence interval, then we lack evidence to disclaim the possibility that the point estimate is the same as the compared value. In other words, if the point estimate is 51%, and the 95% error margin is +/- 3%, then we wouldn't have sufficient evidence to disclaim the possibility that the true population value was, say, 49%. Let's say, however, that 47% were important for some reason. Given that 47% falls outside our confidence interval, we would say that if the true population value were 47%, it would be highly unlikely that we'd conduct our poll and produce a result of 51%. We'd therefore disclaim or reject the possibility that the true value in the population is 47%.

Note that we can't *rule out* the possibility that Biden's actual job approval in the broader population is 47%. It is just that producing a poll with a 51% result if the true population were 47% is sufficiently unlikely, given the standards of modern social science, that we would reject the possibility.

The other way that we can interpret a poll is with a traditional hypothesis test, or p-value. The p-value tells us the probability that we would see a result as extreme or more extreme than the sample result we observe if the opposite of our hypothesis were true. Traditional social science demands a p-value of lower than 0.05, which corresponds to 95% confidence. Results are sometimes published with p-values approaching 0.1, which corresponds to 90% confidence. It would be rare for results to be published with p-values greater than 0.1 Note that in truth confidence intervals and p-values measure the same thing; if a value falls within the 95% confidence intervals, the p-value will be larger than 0.05. One respected statistics text explains this way: "Typically researchers use the following scale:

p-value < 0.01: very strong evidence against H_0

0.01- 0.05: strong evidence against H_0[3]

0.05 – 0.1: weak evidence against H_0

$>$0.1: little or no evidence against H_0

Larry Wasserman, *All of Statistics: A Concise Course in Statistical Inference* 156-157 (2004) (footnote added).

One critical thing to understand here: Classical statistical inference works in a counterintuitive manner. To put it in trial terms, it is not "the fact that we see X, Y and Z makes it clear that the accused is guilty." We never make statements directly about the probability of an outcome in classical statistics. Instead, we operate on the basis of an argument about the chances of getting the type of evidence we observe if our theory were not true.

In other words, the logic proceeds along the lines that "if the accused were innocent, he wouldn't have done X, Y and Z. It's just too unlikely that we'd get this type of evidence if he were innocent, so you must find him guilty." In other words, if the theory is "the CVAP in this district is above 50%" we ask ourself "If the CVAP were at or below 50%, how likely is it that we would have obtained this poll result.[4] If it's extremely unlikely, we would reject a suggestion that the CVAP were at or below 50%. If, however,

[3] H_0 is how we denote the "null hypothesis," or the opposite of our hypothesis. Let's say our hypothesis is that "the Black CVAP of the district is higher than 50%." The null hypothesis would be that "the Black CVAP of the district is not higher than 50%." Using this standard, a p-value of greater than 0.1 would be considered "little or no evidence against this null hypothesis." In other words, the ACS data would reflect little or no evidence against a claim that the Black CVAP of the district is not higher than 50%. Because we lack sufficient evidence against that opinion, we would not rule it out, and would not, using standards typical of the social sciences, be able to claim that the Black CVAP of the district was above 50%. Because p-values and confidence intervals measure the same thing, we could also say that a value that falls within a 90% confidence interval has a p-value in excess of 0.1.

[4] It is true that the point estimate is the "maximum likelihood estimate," or MLE. It can be thought of as a "best guess" of the data. There are two important caveats. First, the "best guess" is not the same as "more likely than not." Second, it is still a statement about the likelihood of the data, rather than the actual value of our parameter. See Wasserman at 122-24. This is almost a truism: What's the most likely population value that would bring about a poll result of 51%? The most likely population value to produce that poll result would be 51%. That still, however, doesn't tell us much about the probability that the true population value is 51% as many other population values can easily lead to a point estimate of 51%.

obtaining a sample showing a given CVAP is something that could easily occur through the vagaries of sampling, we wouldn't reject the suggestion that the CVAP were at or below 50%.

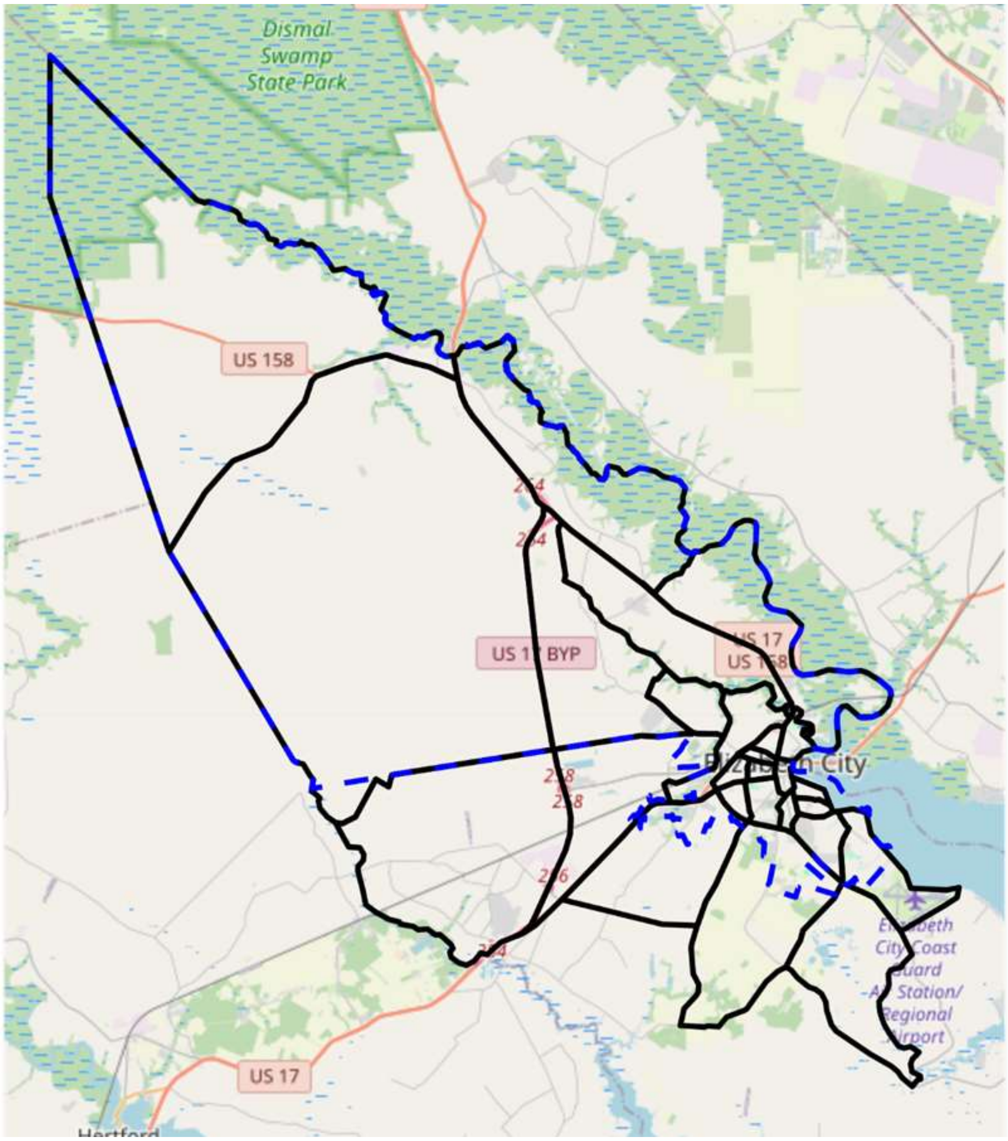
Remember, in classical statistics – which is the approach that the Census Bureau discusses using in its *Handbook* – we never make direct statements about the likelihood or probability that the hypothesis is true; a p-value of 0.2, for example, does not mean that the hypothesis has an 80% likelihood of being true. It's a statement about the probability of receiving the data assuming the hypothesis is false. In other words, it is more about the reliability of the evidence itself and whether it comports with social scientific standards.

5.1.5 The relationship between block groups and precincts.

Finally, in our discussion of the census geographies above, it should be noted that one geography is missing: precincts. This is because precincts are not created by the U.S. Census Bureau. There is a geography called VTDs, which are generally close to the 2022 precincts, but do not necessarily match up with those precincts. Precincts and VTDs typically follow the lines of Census Blocks. They do not, however, always follow the boundaries for block groups. This creates problems for ACS results in the election context, given that those results are only reported down to the Block Group level.

To better understand this, examine the following map. The block groups in Pasquotank County crossed by Esselstyn's Illustrative Map B-1 are illustrated with solid black lines, while the district boundary itself is illustrated by a dashed blue line.

Figure 2: Block Groups in Pasquotank County,North Carolina, with district lines superimposed.

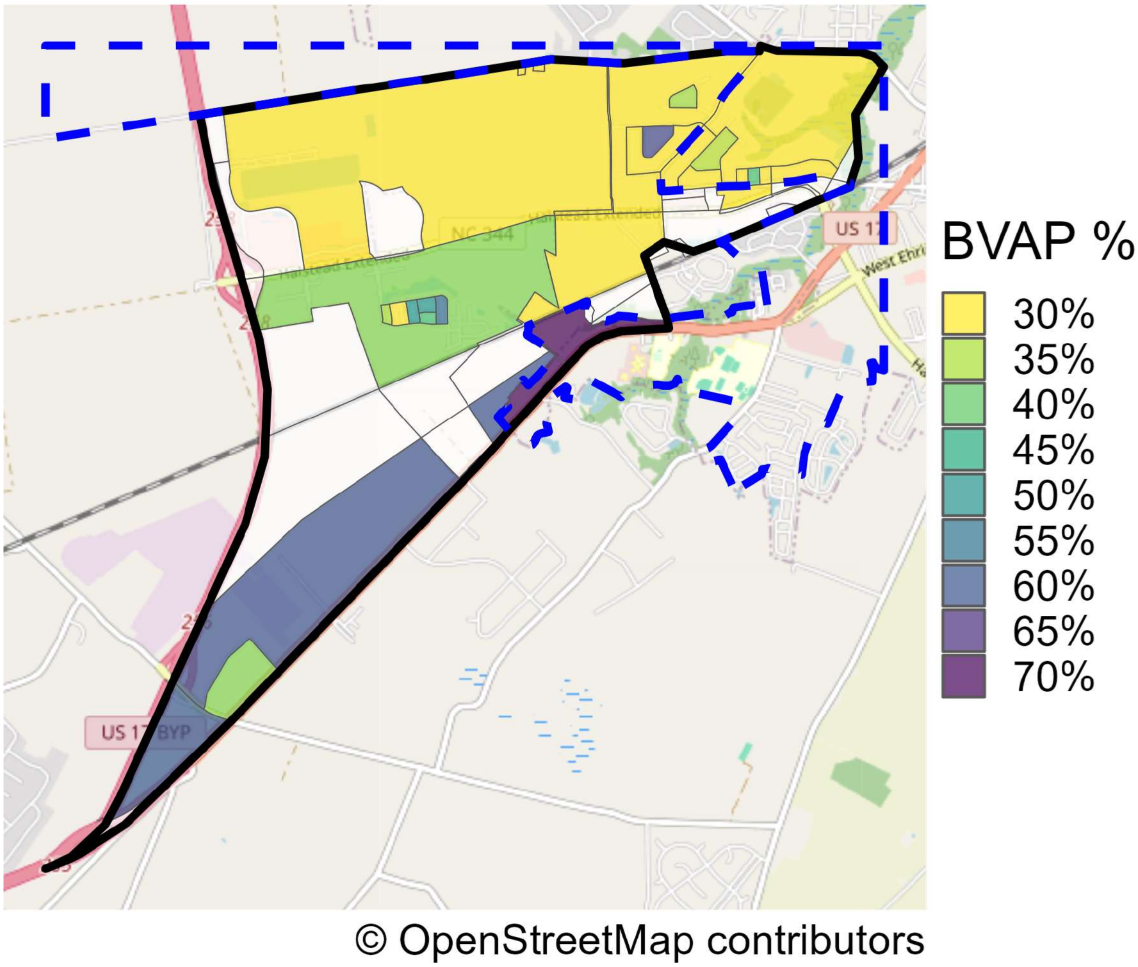


As you can see, there are times where the district boundary does not adhere to any Block Group boundary. In other words, at times the district splits block groups. Because CVAP data is only reported down to the block group level, and because block group data do not always line up with precincts, we must often estimate what portion of the CVAP of a given block group is included in the district and which portion is not.

There are techniques to do so, but they only provide estimates. Moreover, those estimates do not have known error margins or published failure rates. While the specifics of these techniques vary, they are typically variations on a theme. I will describe below the technique utilized by the Redistricting Data Hub, since Mr. Esselstyn and I both rely upon those data here.

To understand this, consider another map, which depicts one of the block groups that is split by Esselstyn Demonstrative District B-1.

Figure 3: Split Block Groups, Esselstyn Illustrative Map B-1



This block group has an overall estimated CVAP of 920, and an estimated Black CVAP of 105.[5] The 90% error margin for the overall estimate is +/- 315 citizens and the corresponding error margin for the Black CVAP estimate is +/- 149 Black citizens. The error margins at 95% confidence are +/- 373 and +/- 178, respectively.[6]

[5]Note that "Black" for purposes of CVAP is defined here as "Black Alone," "Black or White in combination" or "Black and American Indian."

[6]A discerning eye may notice that the error margin would fall below zero, which is obviously impossible. The census advises simply truncating the lower bound at zero, to eliminate impossible outcomes.

The portion of the district that crosses the block group is depicted with a dashed blue line. Then, the block groups contained within the district are filled in by their percent Black Voting Age Population, taken from the decennial census.

The goal is to allocate the estimated 920 total citizens and 105 Black citizens in the block group to those who reside within the district and those who reside outside the district. As the file titled "README.txt" explains, for each block contained within the block group, the CVAP estimate for a given demography is allocated according to the population of the block. In our example here, we calculate, for each block, the percentage of the block group's VAP contained in the block, and the percentage of the block group's BVAP contained within the block. The block group overall has a VAP of 1212 and a BVAP of 346. Census Block 371399606002000, contained within the block group, has a VAP of 127 and a BVAP of 12. It therefore contains 10.5% of the block group's VAP and 3.5% of the block group's BVAP. The CVAP is then assigned to the Census Block using these ratios. In other words, it is assigned 920 x .105 = 96 citizens and 105 x 0.035 = 3 Black citizens. The blocks that are contained within the district's boundaries are then aggregated together.

There are four issues with this. First, this assumes that the CVAP for each racial grouping is distributed in the same way as the VAP, which may or may not be true. In other words, while Census Block 371399606002000 may have exactly 3.5% of the block group's total VAP, it doesn't necessarily follow that it will have exactly 3.5% of the block group's total CVAP. That census block may have a disproportionate share of a Block Group's Hispanic immigrant population, for example. Unfortunately, we have no way of knowing what this failure rate actually is. This introduces additional uncertainty beyond what we can ascribe to error margins.[7]

Second, our allocation is based on the point estimate for the Block Group's CVAP.

[7] Normally we would say that this wouldn't matter in the aggregate, since the errors will likely cancel out (i.e., sometimes it would be low, and when we put it all together the total error rate is zero), using something like the Weak Law of Large Numbers. The problem is that this assumes that the errors are actually randomly distributed. But because we don't even know the error rate, we can't validate this assumption. In fact, we have good reason to believe that they are not randomly distributed, since populations are often geographically clustered together in non-random fashion.

But as described above, these point estimates come with error margins, which can be sizeable at the Block Group level. For example, the estimated Black CVAP for the block group is 105, but it comes with a 90% error margin of +/- 149. We couldn't rule out the possibility that the Black CVAP of the Block Group is 254, nor could we rule out the possibility that it is 0. In other words, by basing our allocation off of an estimate with a substantial error margin, we could well be artificially inflating or deflating the CVAP of the district.

Third, differential privacy complicates this endeavor. Beginning with the 2020 census, data at the block level were randomly altered to mask individuals' identities, including racial data. `https://www.ncsl.org/technology-and-communication/differential-privacy-for-census-data-explained#:~:text=Differential%20privacy%20will%20mean%20that,used%20to%20protect%20small%20populations`. This means that the weights used to allocate the Black CVAP may be inaccurate. We have no way of knowing.

Fourth, when we group the Block Group CVAP estimates together for complete block groups to form larger geographies, such as counties or Illustrative Districts, we know how to estimate the error margins. See *ACS Handbook*, Ch. 8. When we disaggregate the data, however, that information is lost; there's no known way to estimate the error margins downward. This all may be unimportant in most settings, however when a specified threshold holds legal significance, the importance is likely increased. Regardless, even setting aside the first issue here, there's no way to estimate the CVAP error margin due to sampling error for an entire Illustrative District. I will provide the error margins below for all of the Block Groups in the district. However, because the population of the district is smaller than the populations for all of the block groups in the district, and because error margins are inversely related to population, the actual error margin for the district will likely be somewhat larger. In other words, the numbers provided below reflect something of a "best case" scenario for plaintiffs.

5.2 Illustration of Esselstyn maps

This section provides illustrations of Mr. Esselstyn's maps. Each map shows the outlines of the districts that are changed from the Enacted Map. County boundaries are illustrated through blue dashed lines. Analysis of the maps follows in subsequent sections.

Figure 4: Esselstyn Illustrative District A

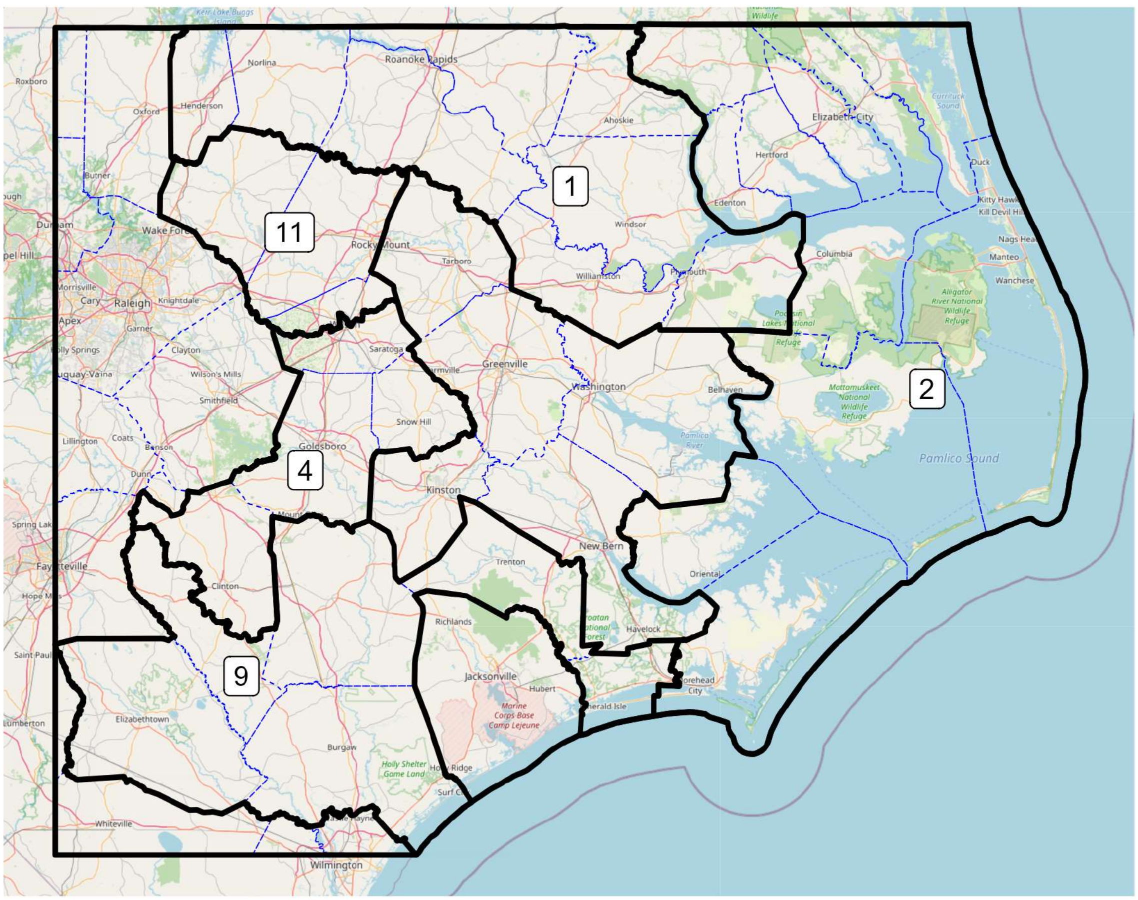


Figure 5: Esselstyn Illustrative District B

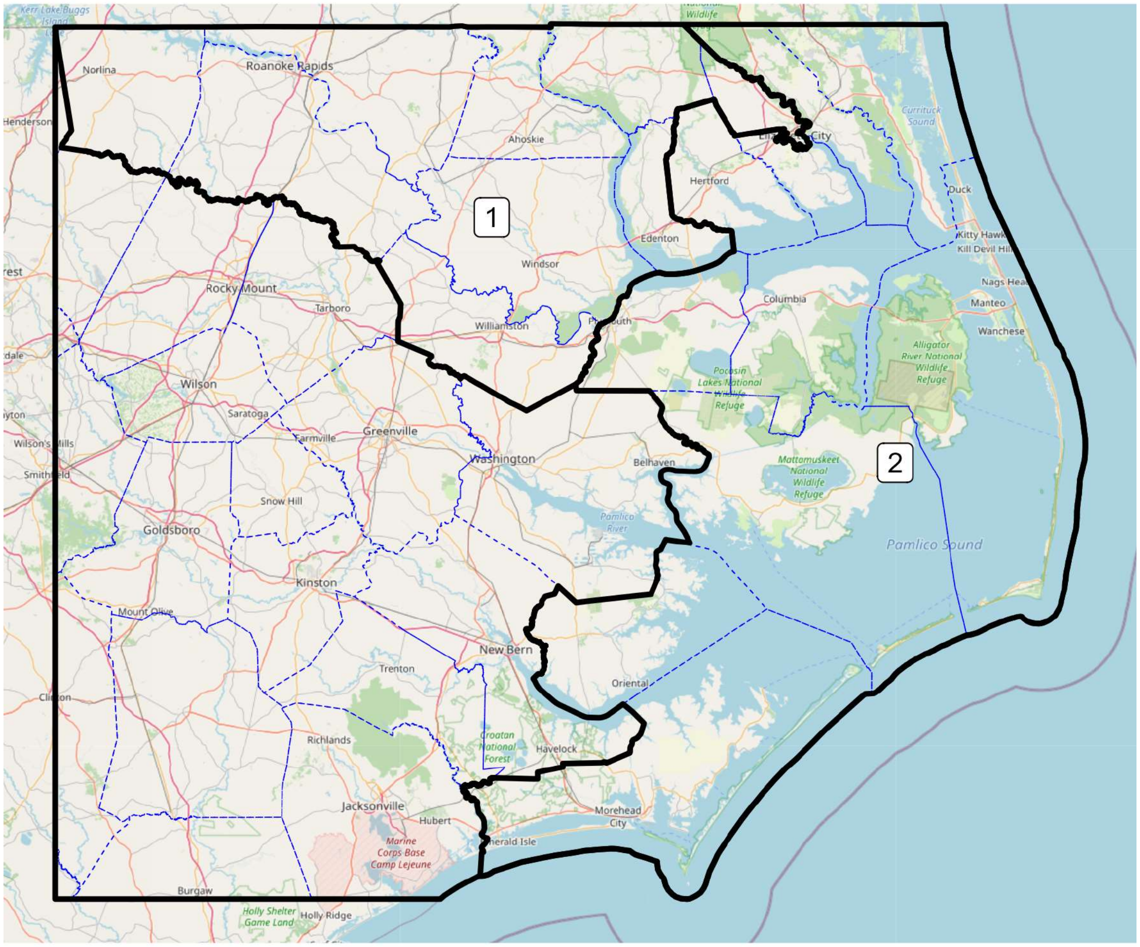


Figure 6: Esselstyn Illustrative District C

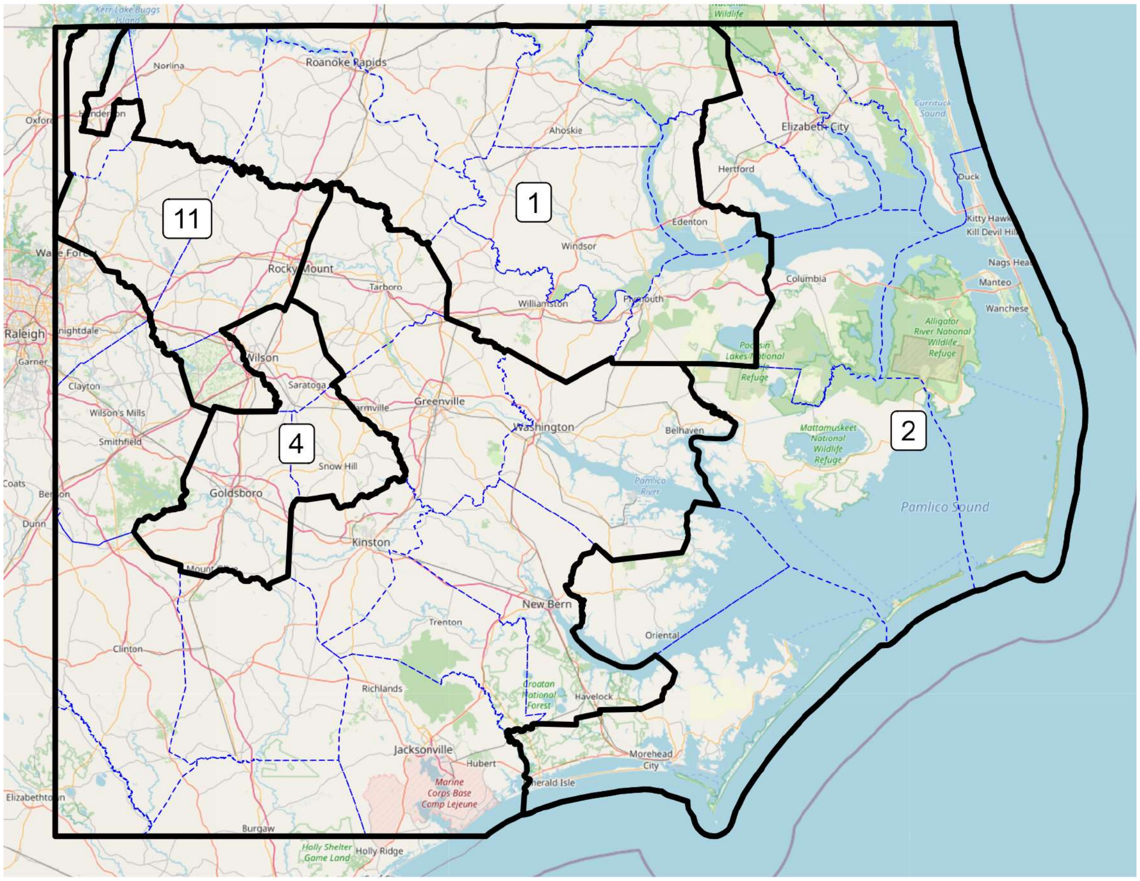
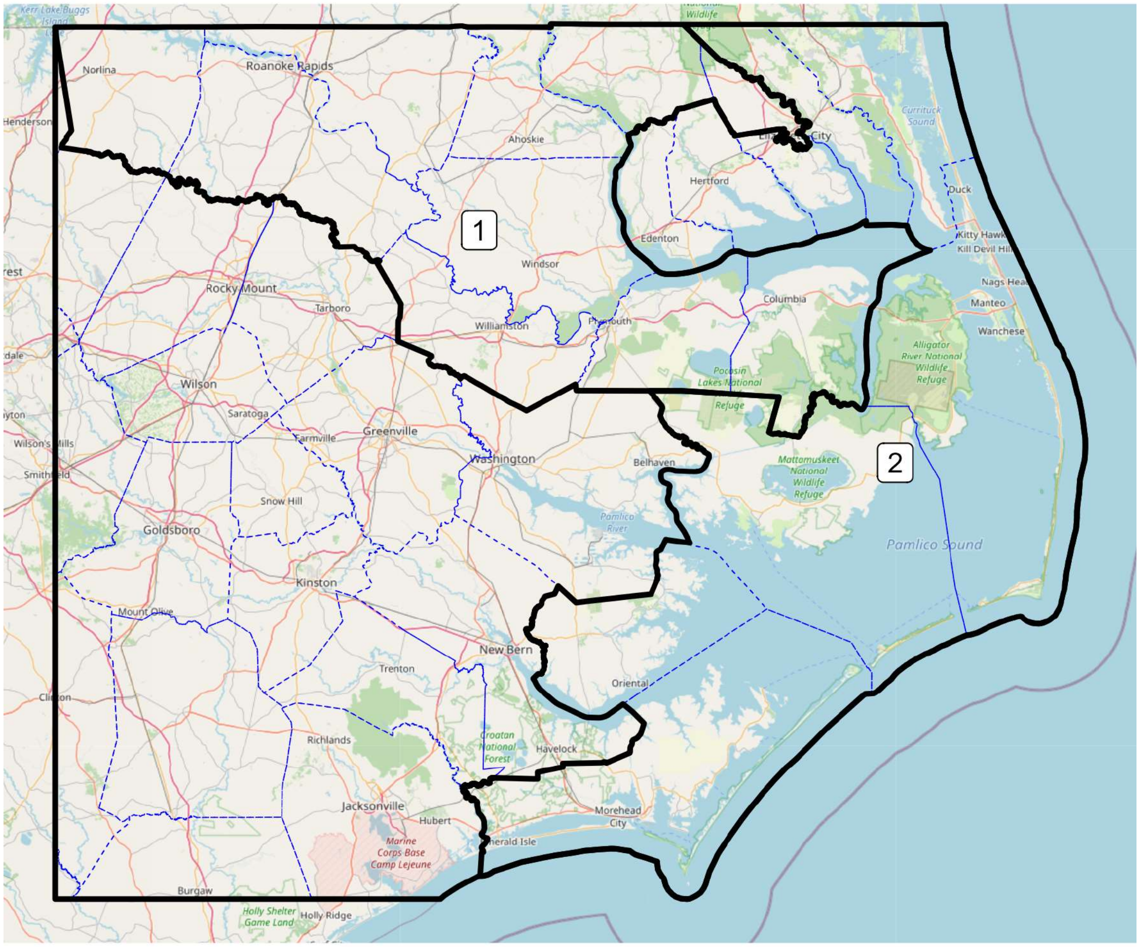


Figure 7: Esselstyn Illustrative District D



These maps all involve changes to the existing *Stephenson* groupings. Maps A and C obviously change the groupings by extending District 1 into Vance County. Maps B and D combine the single district groupings that comprise Enacted District 1 and Enacted District 2 into a single county grouping and split Pasquotank County.

5.3 We cannot say with a reasonable degree of scientific certainty that Districts B-1 and D-1 are majority Black CVAP

5.3.1 Mr. Esselstyn cannot say with a reasonable degree of certainty that district B-1 has a majority Black CVAP using population estimates centered on 2020

As explained above, the 2020 ACS data were not collected in 2020. Instead, they are aggregated data that were collected from 2016 to 2020. Mr. Esselstyn bases his report on the 2020 CVAP data. *See Esselstyn Report*, Attachment B.

The 2022 data, however, have been publicly available for several months. An estimate at the block level was uploaded to the Redistricting Data Hub, from which Mr. Esselstyn obtained his data, *id.*, on June 24, 2024. See `https://redistrictingdatahub.org/state/north-carolina/`. The 2022 data are aggregated from the years 2018, 2019, 2020, 2021 and 2022. They are therefore centered on 2020. I have downloaded the block-level estimates (estimated using a version of the techniques described above) that were made available via the Redistricting Data Hub. From this, we can estimate the 2022 Black CVAP. The estimated CVAP for the district is 157,022 and the estimated Black CVAP is 77,588. The point estimate for the percent Black CVAP using the 2022 data is therefore 49.4%, less than 50%.

5.3.2 Mr. Esselstyn cannot say with a reasonable degree of certainty that districts B-1 and D-1 have majority Black CVAPs

Even using the 2020 data, Mr. Esselstyn cannot say with a reasonable degree of certainty typical of the social sciences that districts B-1 and D-1 have majority Black CVAPs. The total estimated CVAP for the block groups in district B-1 is 169,225. The total estimated Black CVAP for the block groups in district B-1 is 83,992. The estimated error margin for the block groups in District B-1 is +/-2.1% for the traditional 95% confidence (values falling within this range would be associated with a p-value of greater

than 0.05) or +/-1.8% for the census-reported 90% confidence (values falling within this range would be associated with a p-value of greater than 0.1).[8] As explained above, this is a bit more generous than the likely error margins for the actual district. Since Mr. Esselstyn's reported Black CVAP is 50.19%, we would not conclude that the Black CVAP percent in this district is above 50%. Additionally, the overall Black CVAP % of the block groups in the district is 49.6%. In other words, even the claim that the overall estimated Black CVAP % for the district is above 50% is dependent upon the error rate for the method for allocating split block groups, about which we are unsure.

Using the 2022 CVAP data, which is centered on 2020, Mr. Esselstyn's District D-1 has a Black CVAP above 50%, albeit barely. The estimated Black CVAP percent using the 2022 reporting is 50.14%. The error margins for the Black CVAP estimate using the 2020 data for the block groups in District D-1 are +/- 2.1% at 95% confidence, and +/- 1.7% at 90% confidence. The error margins for the Black CVAP estimate using the 2022 data for the block groups in District D-1 are +/- 2.2% at 95% confidence, and +/- 1.8% at 90% confidence. For 2020 the block groups do have an estimated BCVAP above 50% (50.2%), but for 2022 they do not (49.5%), so for that data the claim that the point estimate is above 50% is once again dependent upon the efficacy of the population allocation process for split block groups described above. [9]

[8]Chapter 8 of the *ACS Handbook* explains how to derive error margins here.

[9]Note that a properly equipped researcher could attempt a Bayesian approximation here. This separate branch of statistics (popular at some universities, including at Ohio State), allows us to make direct probability statements about the outcome of interest. For example, a public opinion poll's point estimates and confidence intervals derived by classical statistics are based upon the number of observations (n) and the number of people in a group (call this "r"). Thus, if, in a sample of 500, 200 people approve of Joe Biden's job performance, his job approval would be r/n, or 40%. The confidence intervals can then be derived from that. These results can basically be replicated through a simple beta-binomial model, although the resulting credible intervals are often slightly different than the confidence intervals. Regardless, most social science journals still require 95% confidence to support a claim.

5.4 Configuration of Districts

5.4.1 Esselstyn Illustrative Map A

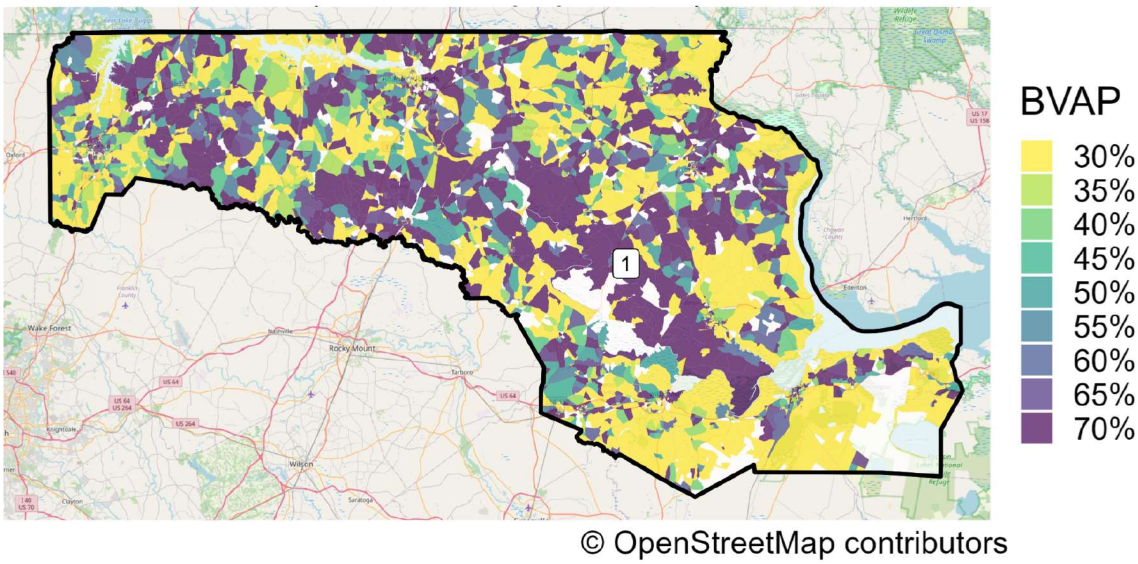
Demonstration Map A, District 1 consists of the whole of Bertie, Halifax, Hertford, Martin, Northampton, Vance, Warren and Washington counties. This configuration requires a reconstitution of the "*Stephenson* groupings" for the State of North Carolina. I discuss this further below.

The district contains 160,510 residents of voting age, of whom 82,610 are Black. Thus, the percent Black Voting Age Population (BVAP) of the district is 51.47%. With a population of 160,510 residents of Voting Age, the district would need to have 80,256 Black residents of voting age to be 50% + 1 Black. Because every county in the district has at least 2,364 Black residents of voting age, all counties in the map are required to achieve a majority Black district. If counties were to be split, which I understand to violate the Stephenson rule, only three precincts at the eastern end of Washington County could be removed while maintaining a BVAP of 50%, or two precincts at the western tip of Vance County could be removed.

I was first asked to create maps that would depict the racial distribution of residents of voting age in Plaintiffs' proposed districts. We begin with choropleth maps. Choropleth maps area traditional "area-based" maps, where some areal unit (here, blocks or VTDs) are shaded to correspond with some data (here, percentage of residents who are Black and of voting age ("BVAP"). We can first look at the maps at the census block level.[10]

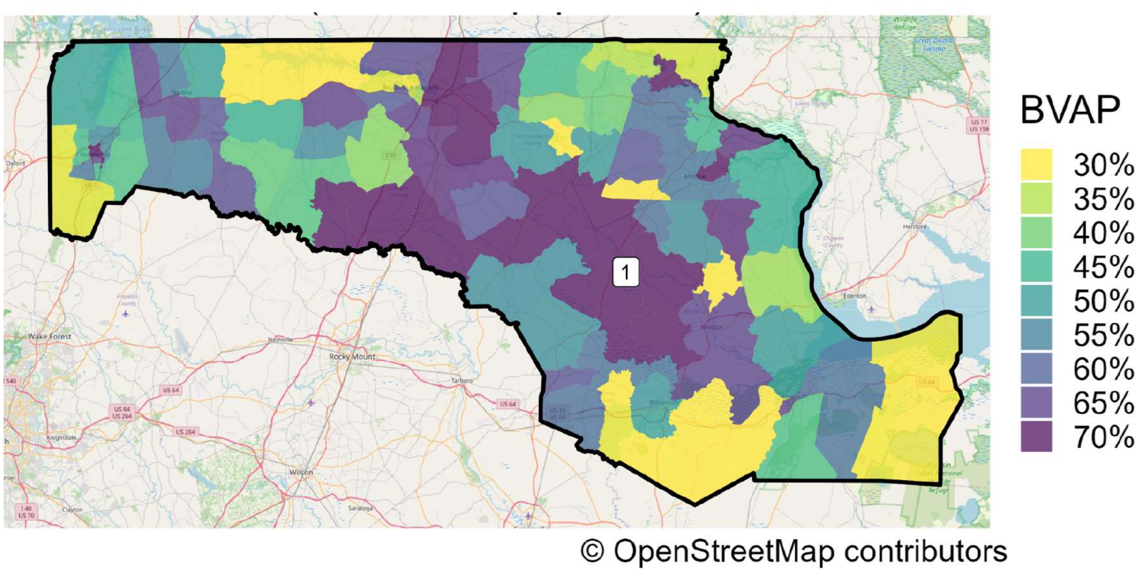
[10]The code for producing these maps is available in the production from the preliminary injunction phase.

Figure 8: District A-1 Block Choropleth



We can also examine the district at the VTD level:

Figure 9: District A-1 Precinct Choropleth

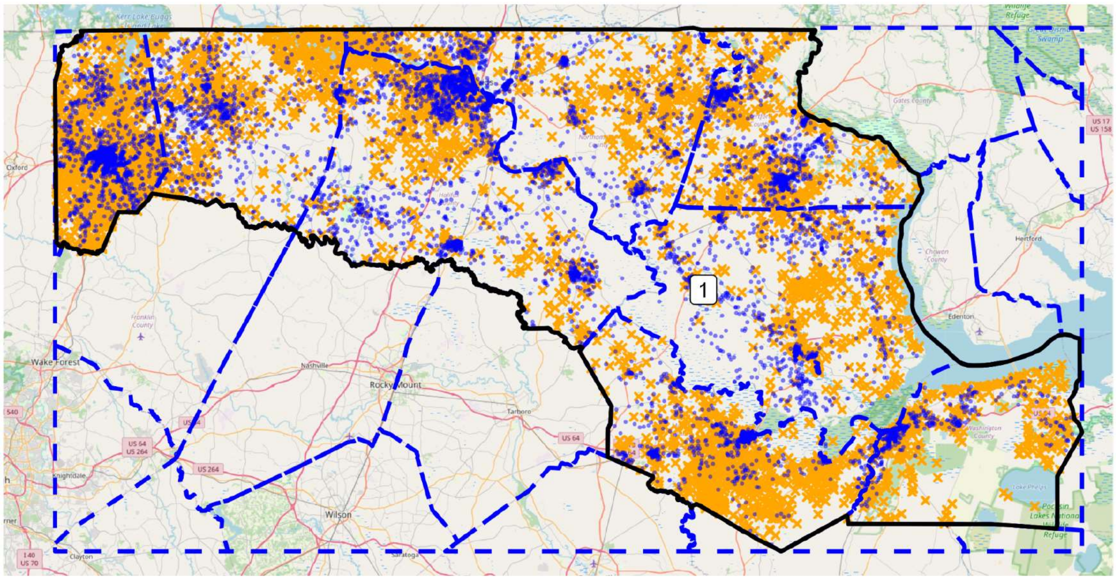


These color scales on these maps are truncated at 30% and 70% BVAP. In my experience, allowing the color scale to run from 0% to 100% risks losing a good deal of data, as differences in the crucial 40% - 60% BVAP range are blended together. This approach has been accepted in many courts in which I have testified, and has never been challenged by a court.

One of the limitations of choropleth maps, however, is that they don't reveal populations. A VTD with 10 Black residents and 10 White residents is treated the same as a VTD with 1,000 Black residents and 1,000 White residents. While there may be times where those differences are immaterial, there may also be times where the difference is important.

To account for this, I will typically employ dot density maps. Dot density maps have been utilized in cases at least back to the Bethune-Hill case, where Dr. Rodden employed them to examine the distribution of residents of districts. In a dot density map, census blocks are taken as the basis for the district. In each block, a dot is drawn for every member of a group, or every ten members, or every 100 members, depending on the scale of the map. For these maps, I employ 1 blue dot for 10 Black Citizens of Voting Age, an orange "x' for 10 White Citizens of Voting Age. Obviously there is some rounding involved, but in the aggregate that typically does not matter. The dashed blue lines reflect county boundaries. Here we see clusters of Black population spread over the countryside.

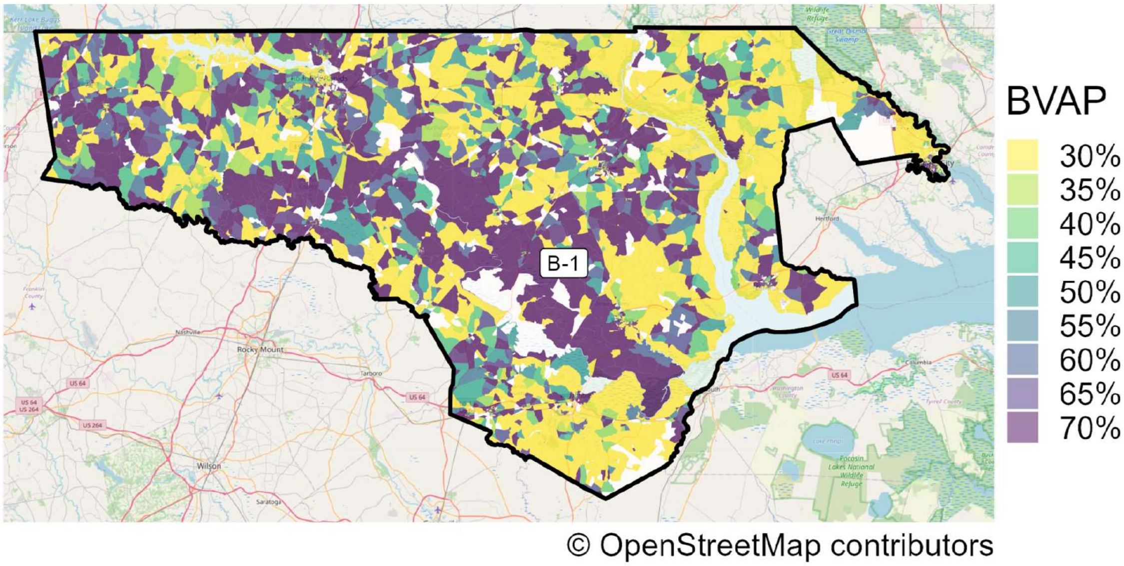
Figure 10: Racial Dotplot, District A-1. One blue dot = 10 Black Residents of Voting Age; One Orange 'x' = 10 White Residents of Voting Age.



5.4.2 Esselstyn Illustrative Map B

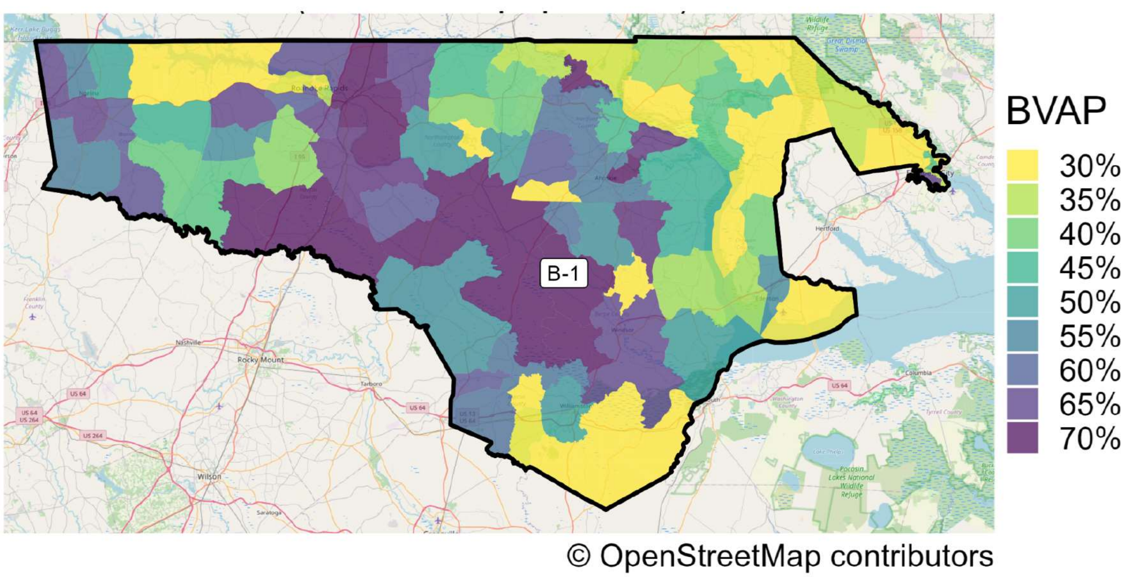
I was also asked to consider the racial distribution of the residents of Map B. District B-1 is the purported VRA demonstration district. Its Voting Age Population is 160,306. Of those, 77,599 residents are Black, giving the district a percent BVAP of 48.4%. Over 11,000 of those Black residents live at the top of the arm of the district that extends into (and splits) Pasquotank County to take in Elizabeth City.

Figure 11: District B-1 Block Choropleth



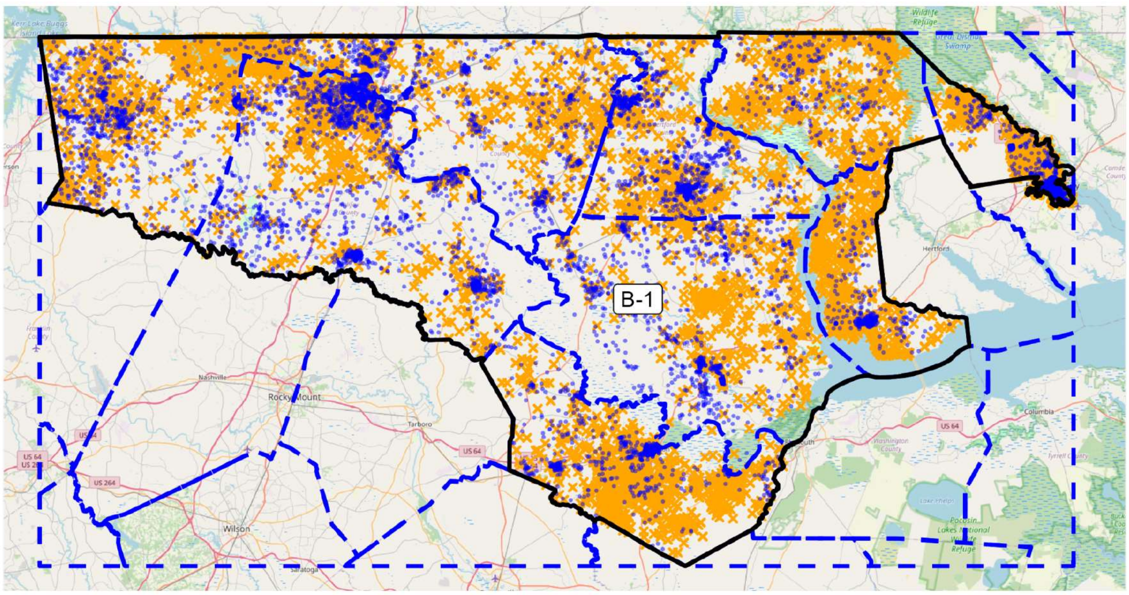
We can also view the data at the VTD level:

Figure 12: District B-1 VTD Choropleth



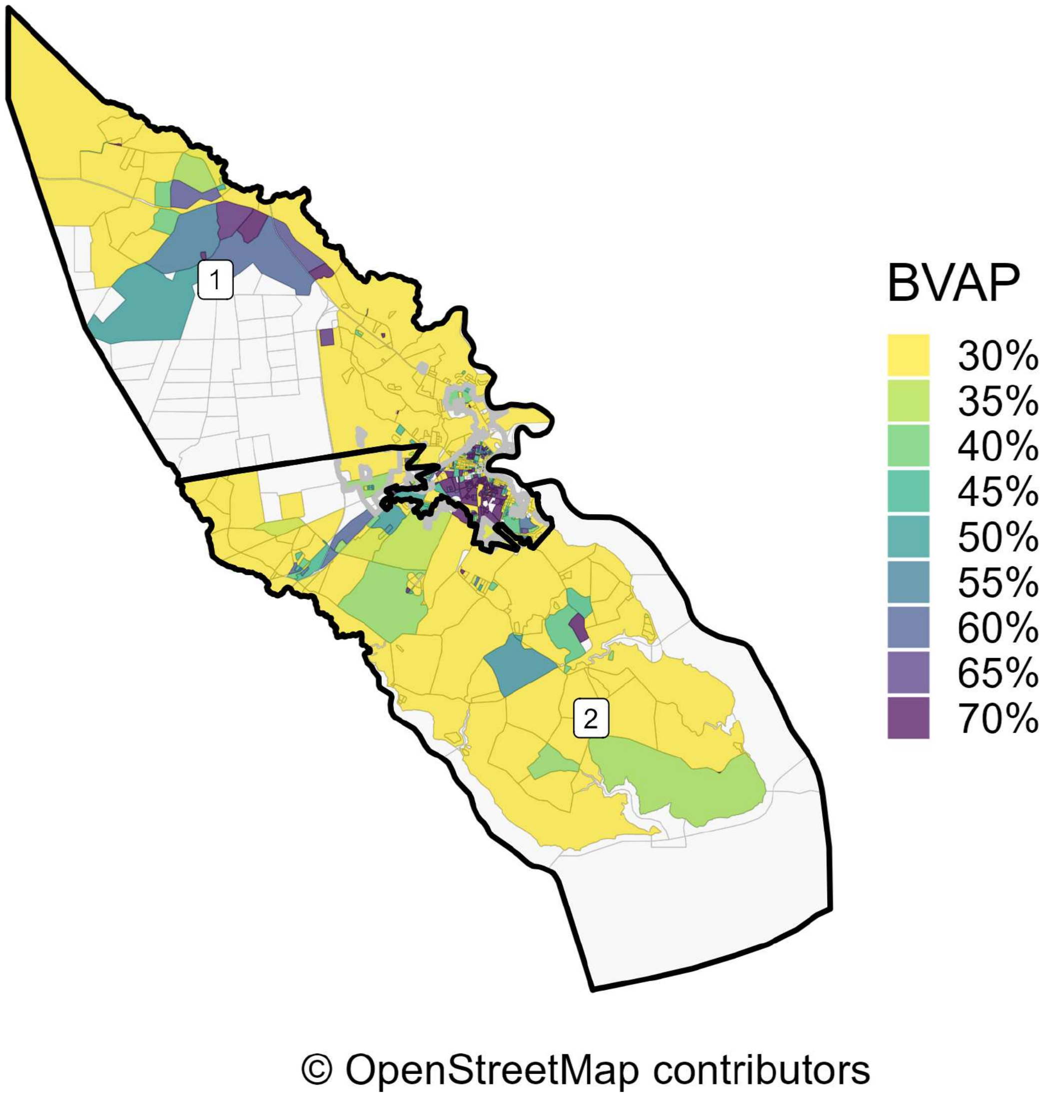
To achieve its majority CVAP status, District B-1 relies on an arm that juts out to grab parts of Elizabeth City. We can better see the distribution of residents using dot density maps:

Figure 13: Racial Dotplot, District B-1. One blue dot = 10 Black Residents of Voting Age; One Orange 'x' = 10 White Residents of Voting Age.



I was also asked to "zoom in" on the split in Pasquotank County. We can once again view this at the census block level:

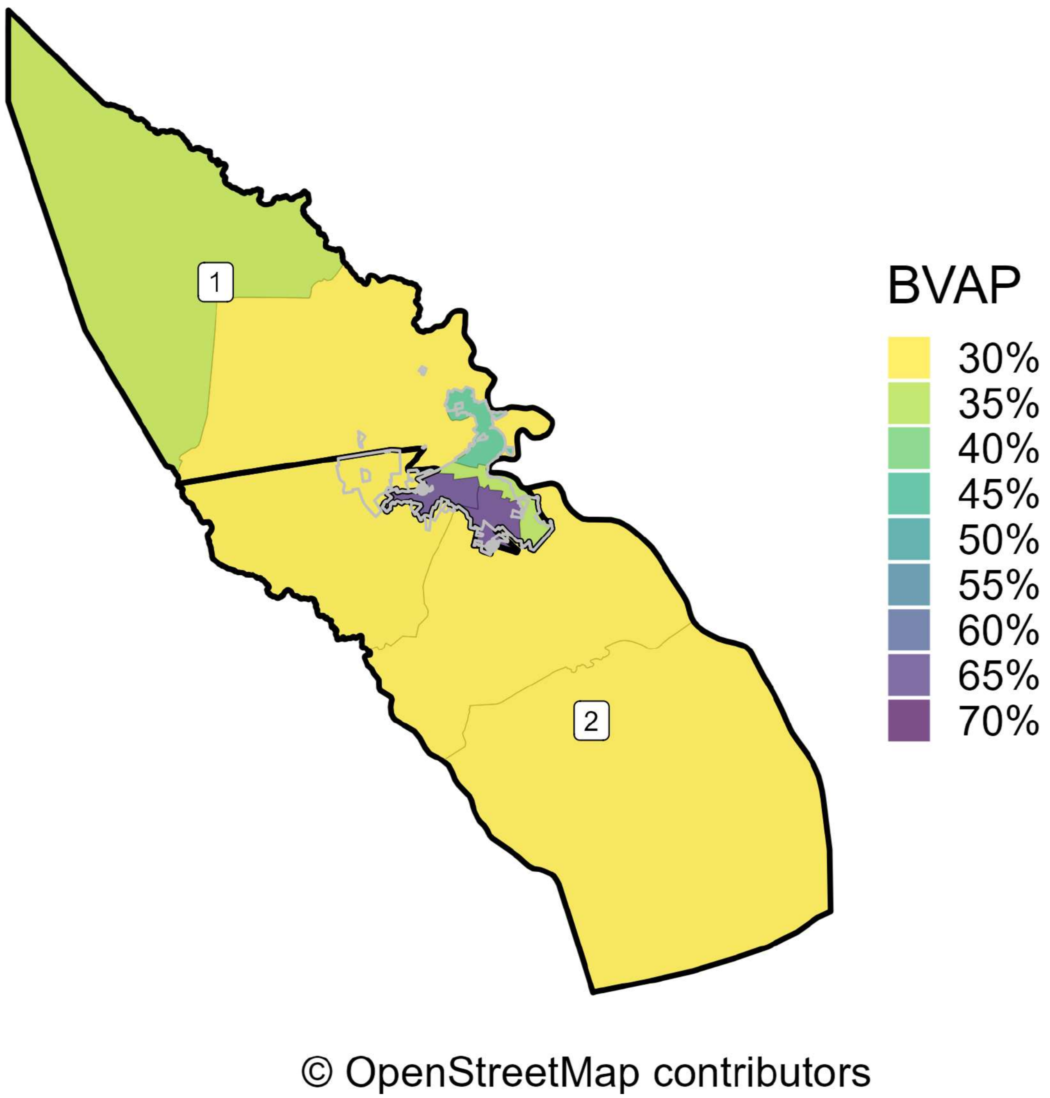
Figure 14: BVAP % of Blocks, Pasquotank County, NC



I was asked to calculate the percent of majority-BVAP blocks placed in District B-1. Of the 989 census blocks in Pasquotank County, 213 are majority BVAP. Of these 213, 194 blocks, or 91%, are placed in District B-1. Of the 11,738 Black residents of voting age, 9,469, or 81%, are in District B-1.

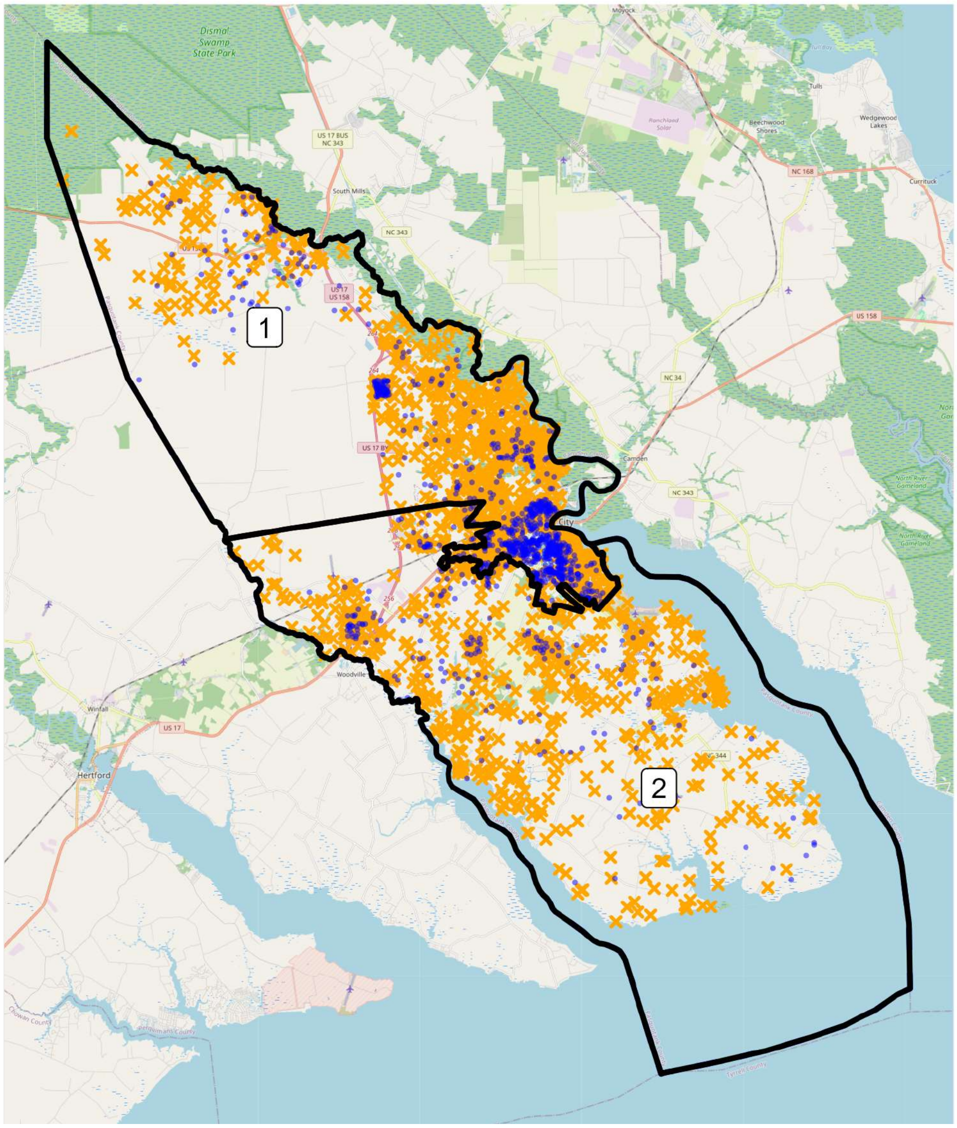
I was also asked to draw the map at the VTD level, with the city boundaries superimposed in grey. The map introduces a split in Elizabeth City.

Figure 15: BVAP % of VTDs, Pasquotank County, NC, with city boundaries and district lines superimposed.



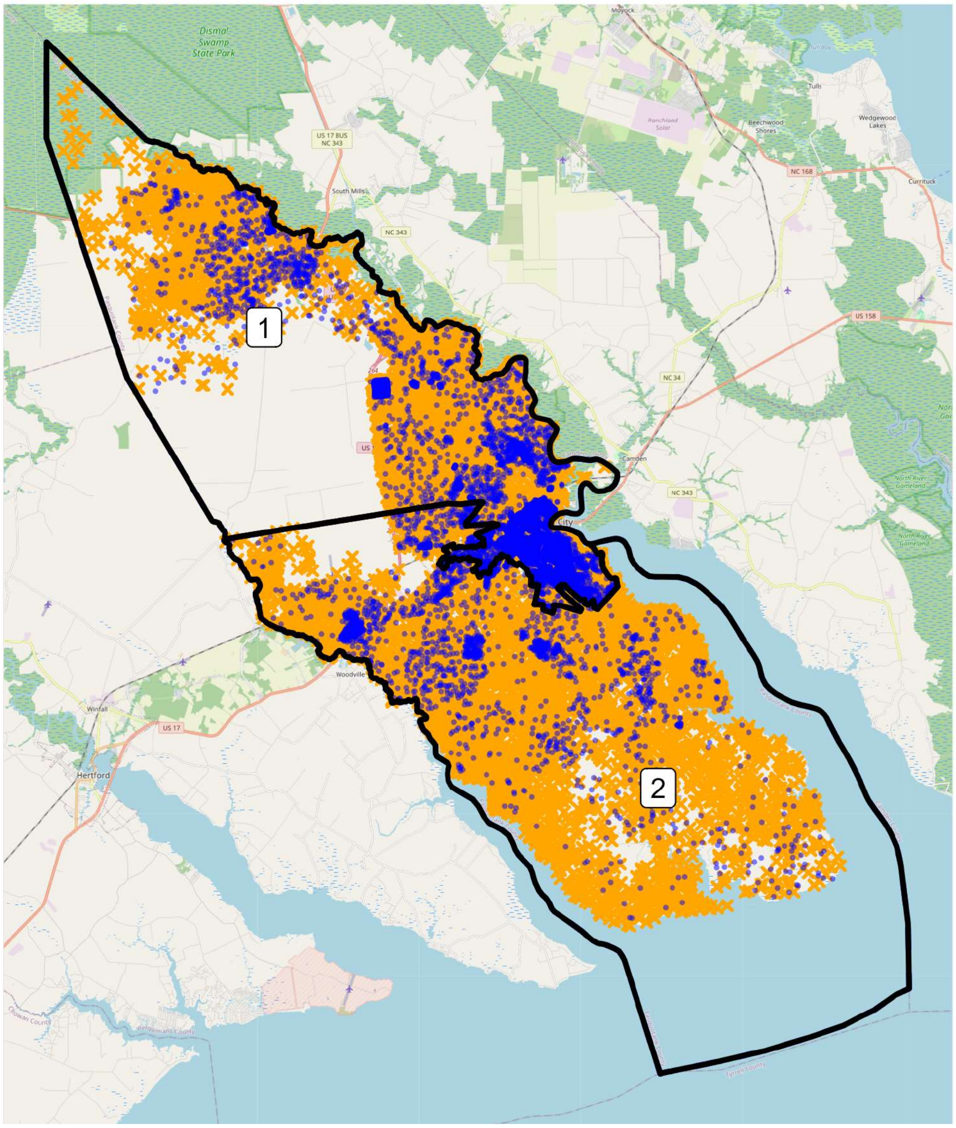
Finally, I was asked to produce a racial dotplot here.

Figure 16: Racial Dotplot, District B-1, Pasquotank County, NC. One blue dot = 10 Black Residents of Voting Age; One Orange 'x' = 10 White Residents of Voting Age.



We can create a similar dotplot where one dot represents one person, though overplotting begins to become an issue, depicted below.

Figure 17: Racial Dotplot, District B-1, Pasquotank County, NC. One blue dot = 1 Black Resident of Voting Age; One Orange 'x' = 1 White Resident of Voting Age.

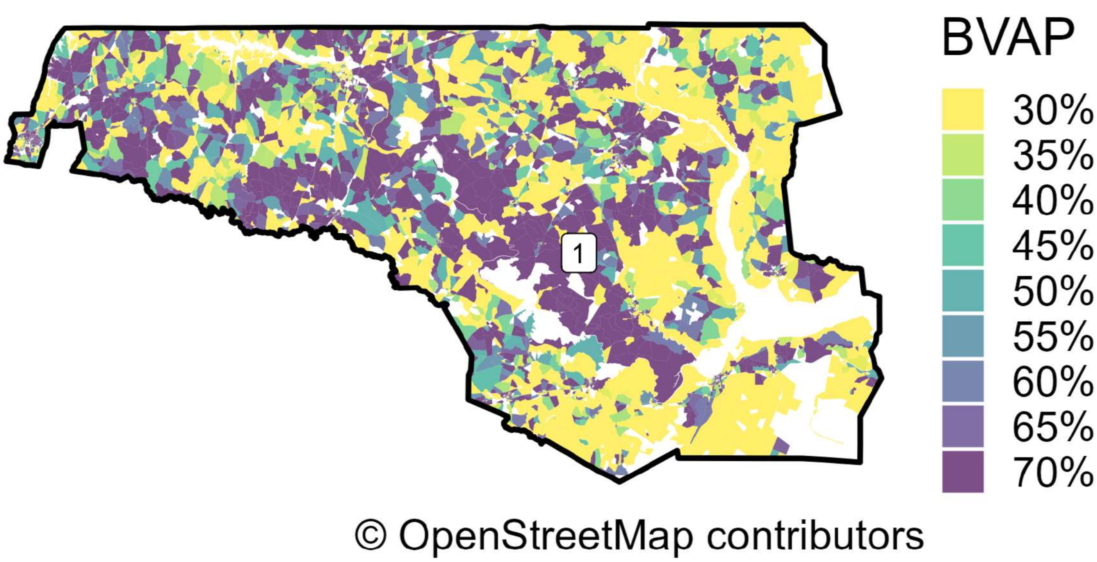


This county split, which barely raises the BVAP of the district above 50%, appears to largely be made on a racial basis.

5.4.3 Esselstyn Illustrative Map C

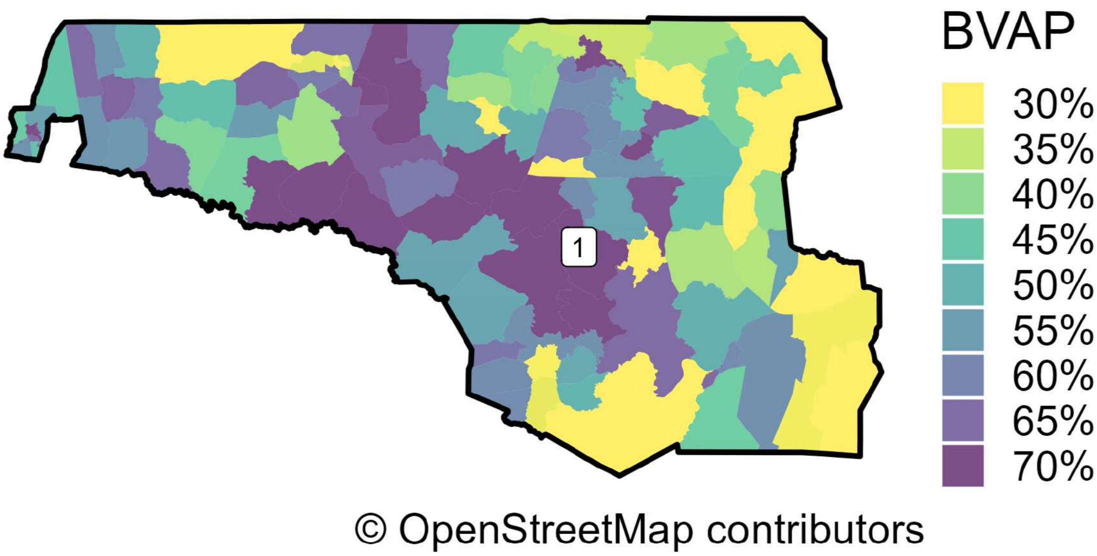
I was also asked to consider the racial distribution of the residents of Map C. District C-1 is the purported VRA demonstration district. Its Voting Age Population is 164,784. Of those residents of voting age, 82,746 residents are Black, giving the district a percent BVAP of just over 50%. Over 10,000 of those Black residents live at the top of the arm of the district that extends into (and splits) Vance County.

Figure 18: District C-1 Block BVAP Choropleth



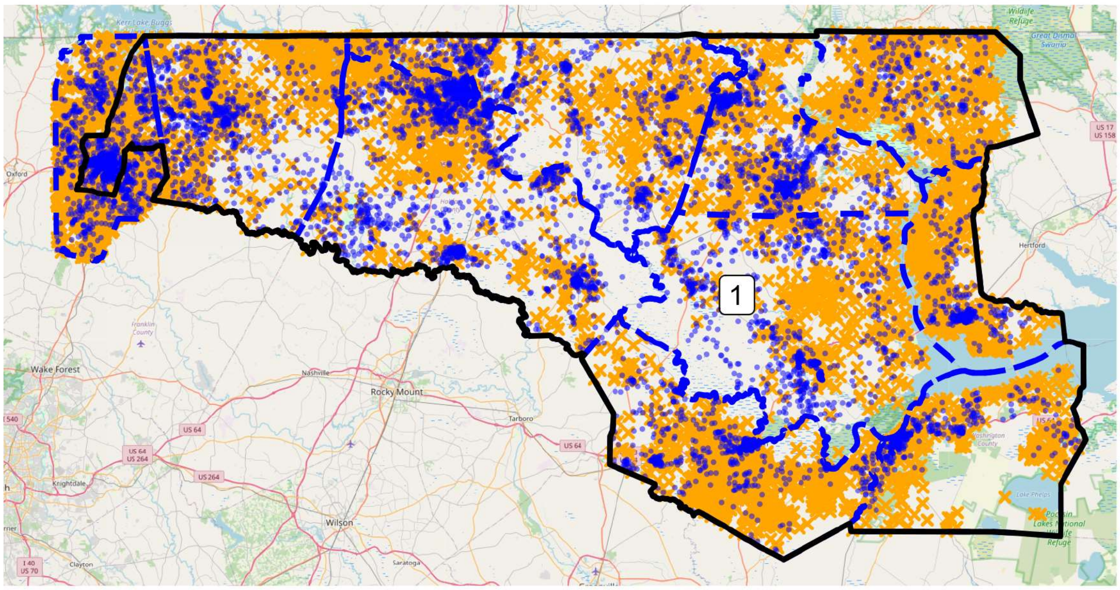
We can also view the data at the VTD level:

Figure 19: District C-1 VTD BVAP Choropleth



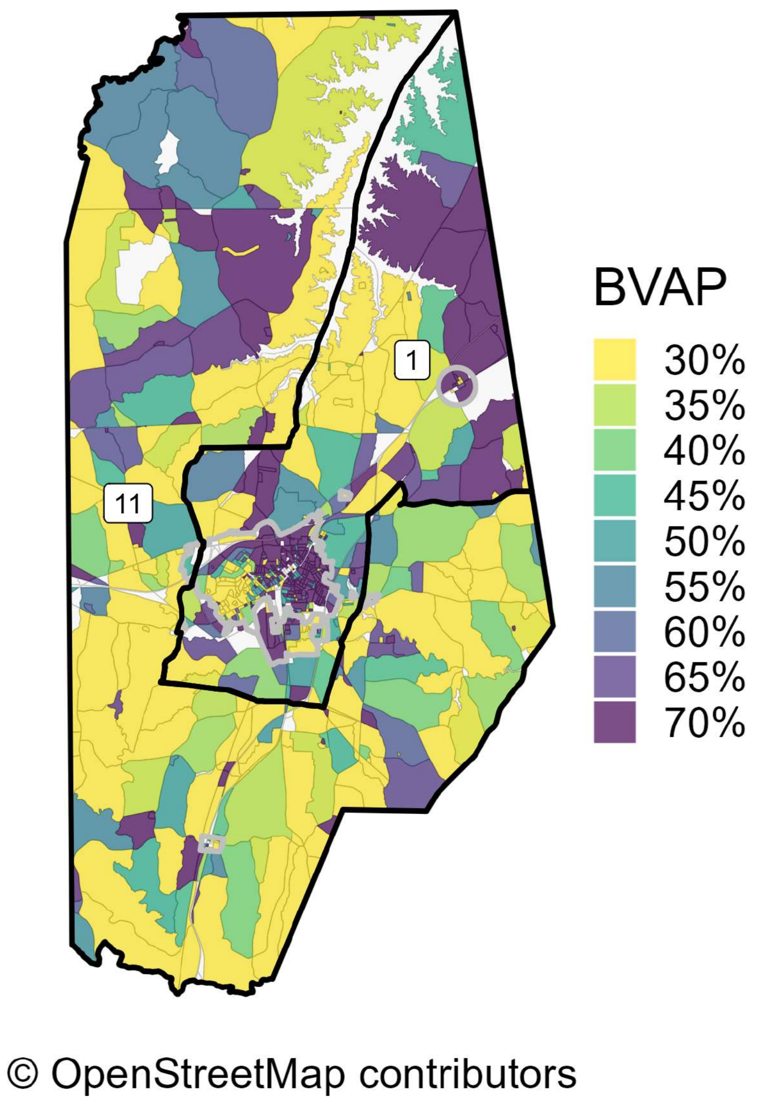
Finally, we can once again better see the distribution of residents using dot density maps:

Figure 20: Racial Dotplot, District C-1. One blue dot = 10 Black Residents of Voting Age; One Orange 'x' = 10 White Residents of Voting Age.



Like Map B, Map C relies upon an arm, this time extending into Vance County, to achieve its racial target. I was also asked to "zoom in" on the split in Vance County. We can once again view this at the census block level:

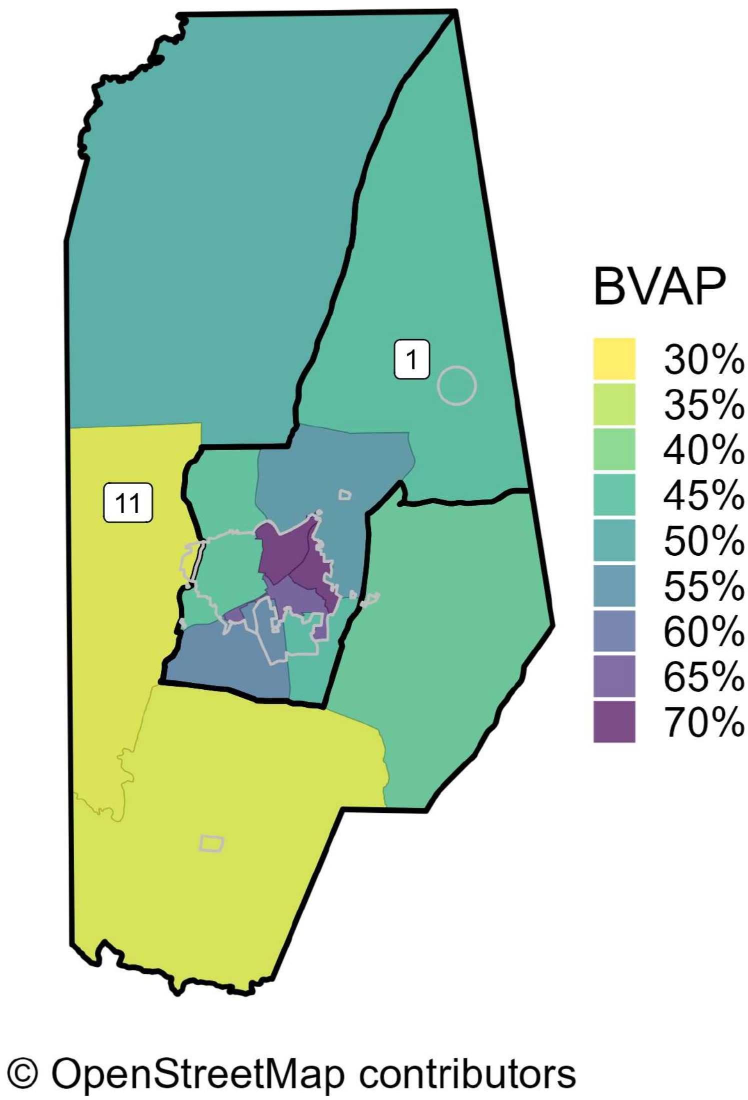
Figure 21: District C-1 Block BVAP Choropleth, Vance County, NC



I was asked to calculate the percent of majority-BVAP blocks placed in District 1, as well as the percent of the Black population of Vance County placed in District 1. Of the 1,125 census blocks in Vance County, 422 are majority BVAP. Of these 422, 332 blocks, or 79%, are placed in District 1. This includes 10,375 of the 16,430 black residents of voting age (63I was also asked to draw the map at the VTD level, with the city boundaries superimposed in grey. Note that Henderson is split. Overall, the odd-looking

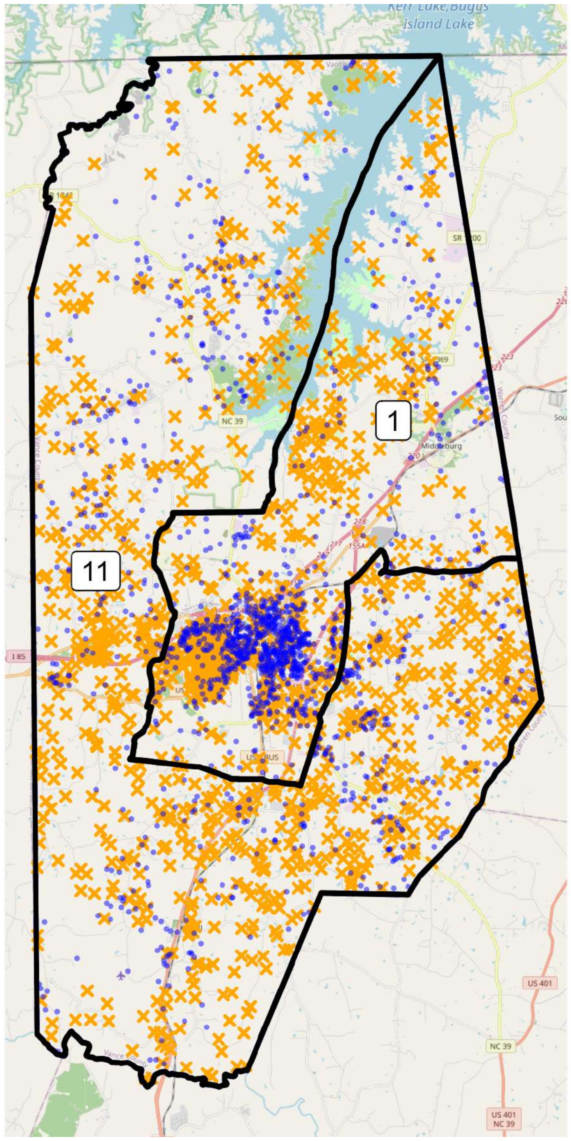
arm separates the Black population of Vance County from the White population.

Figure 22: District C-1 VTD BVAP Choropleth, Vance County, NC



Finally, I was asked to produce a racial dotplot here as well.

Figure 23: Racial Dotplot, District C-1, Vance County, NC. One blue dot = 10 Black Residents of Voting Age; One Orange 'x' = 10 White Residents of Voting Age.



5.4.4 Esselstyn Illustrative Map D

Map D is the same as Map B, except with Chowan County placed in District D-2 and Washington and Tyrrell counties placed in District D-1. It does not require further description here.

5.5 Issues with Dr. Mattingly's County Groupings

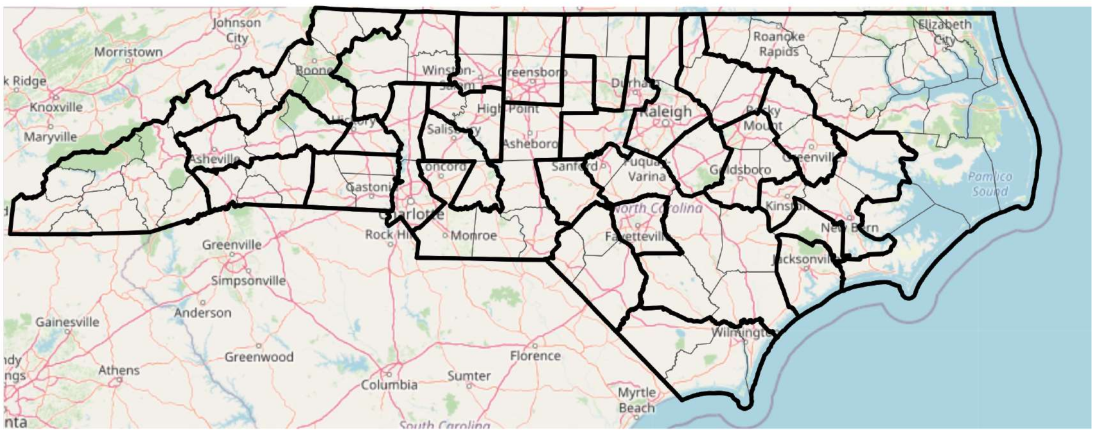
5.5.1 It is not possible to draw a *Gingles I* district in Edgecombe and Pitt counties.

I was asked to determine whether it is possible to draw a Senate district in Edgecombe/Pitt counties where the Black population would constitute a majority of the population. It is not. If we arrange the census blocks in these counties from highest BVAP to lowest and place a sufficient number of blocks in a district (without regard even to contiguity) to raise the population to the minimum population threshold for a state Senate district in North Carolina, the district would still be shy of 50% BVAP. In other words, even without considering contiguity, placing the highest BVAP blocks together with sufficient population to qualify under one-person-one-vote requirements would not cross the *Gingles* threshold.

5.5.2 Dr. Mattingly's County Groupings for Map A rely upon the freeze of Edgecombe and Pitt counties.

The current *Stephenson* county groupings for North Carolina are depicted below. Obviously different groupings may contain different numbers of districts.

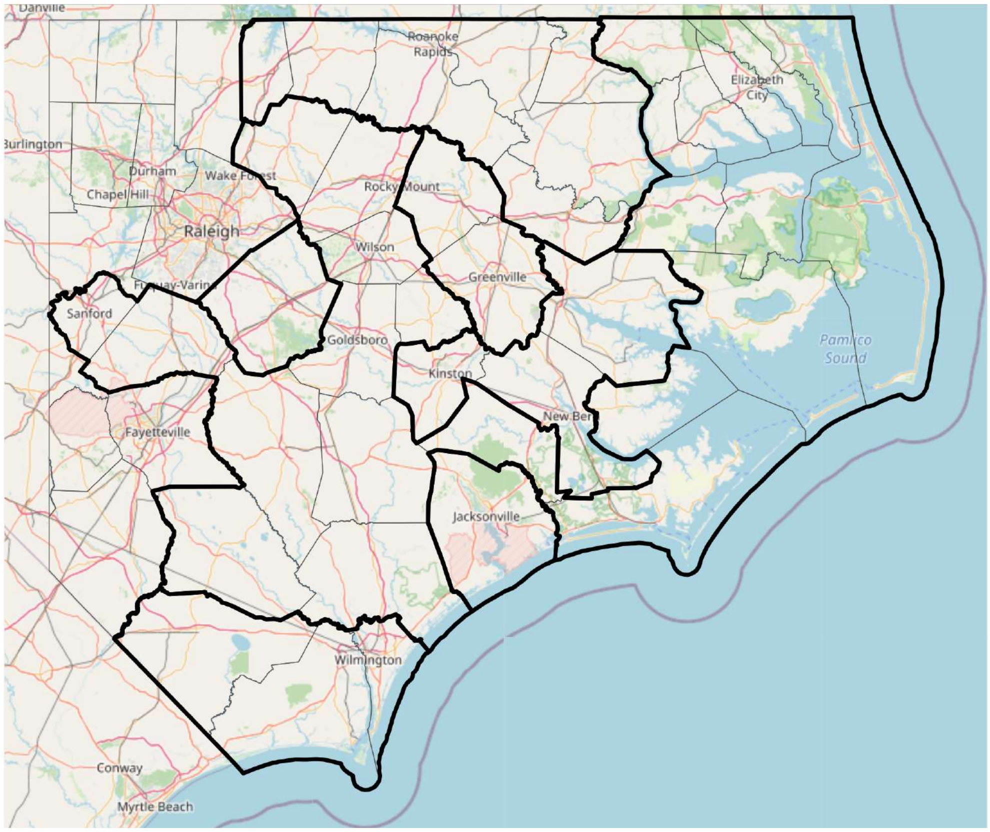
Figure 24: Current *Stephenson* groupings



Dr. Mattingly re-runs his code for determining the optimal Stephenson county groupings for Maps A and C.[11] This run forces Edgecombe and Pitt counties to remain together. For Map A, Dr. Mattingly concludes that Eastern North Carolina should be reconfigured as follows:

[11] He also re-runs them for Maps B and D, but since the demonstration districts in those plans operate within the current *Stephenson* grouping in northeastern North Carolina, with the exception of the merging of groupings 1 and 2, and the Outer Banks, unsurprisingly the results do not change overall.

Figure 25: Suggested *Stephenson* Groupings, Map A



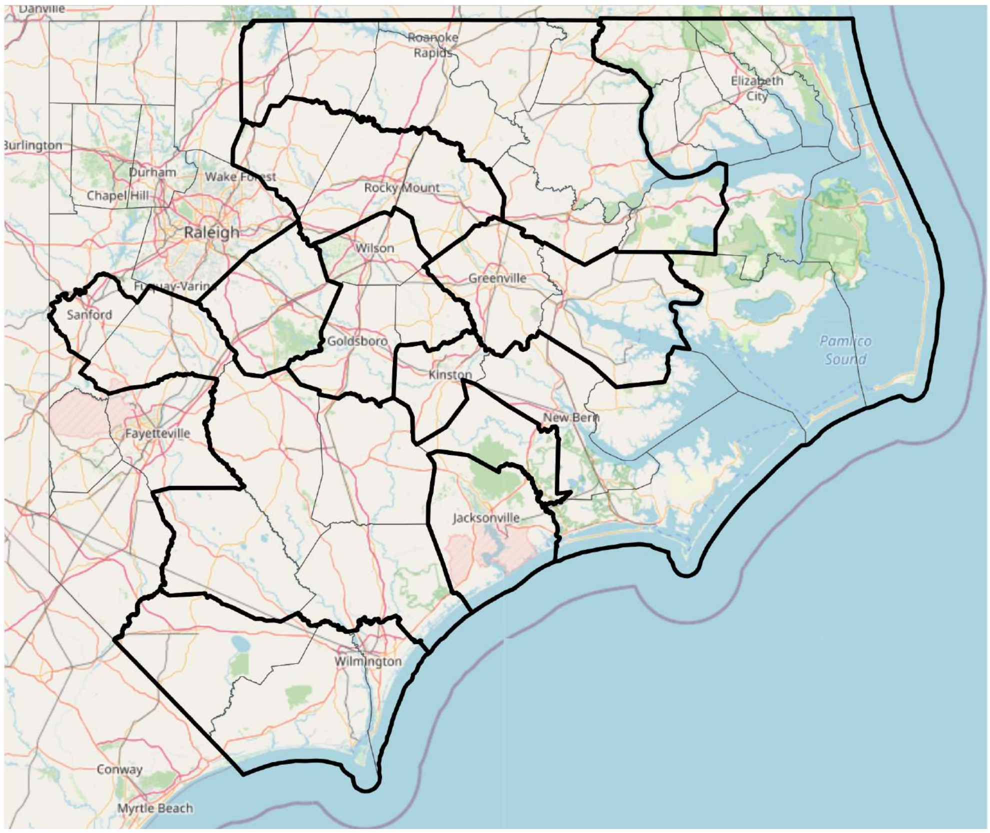
The county groupings that Dr. Mattingly describes effectively create something of an "omnibus" eastern North Carolina grouping by merging together three groupings and a portion of a fourth. This grouping would contain five districts.[12]

I was asked to consider the effect of freezing together Edgecombe and Pitt counties by re-running his code without freezing together Edgecombe and Pitt counties. That is, I was asked to explore whether we would observe the same county groupings if we did not freeze Edgecombe and Pitt. Map C produces the same county groupings as Dr. Mattingly suggests whether or not we freeze together Edgecombe and Pitt. Map A does not. Instead, if we do not force Pitt and Edgecombe together, the naturally occurring

[12]For simplicity's sake, I only display the option that is closest to what the legislature opted for in this case.

county grouping places Pitt County with Beaufort County, while pairing Edgecombe with Nash and Franklin counties. The Stephenson groupings for Map A are therefore as follows if those two districts are not forced to be merged together:

Figure 26: *Stephenson* Groupings, Map A, if Edgecombe/Pitt are not frozen



6 Conclusion

Mr. Esselstyn's maps all change the existing *Stephenson* groupings. Mr. Esselstyn's District B-1 is not majority Black CVAP using the most up-to-date census data. Mr. Esselstyn cannot say with a reasonable degree of scientific certainty that districts B-1 and D-1 have majority Black CVAPs. There is no *Gingles I* district in the Edge-Pittcombe cluster. Finally, Dr. Mattingly's *Stephenson* groupings for Map A depend upon the freezing of Pitt-Edgecombe.

I declare under penalty of perjury under the laws of the State of Ohio that the foregoing is true and correct to the best of my knowledge and belief. Executed on 16 August, 2024 in Delaware, Ohio.

Sean Trende

Sean P. Trende

7 Exhibit 1 – Sean Trende C.V.

SEAN P. TRENDE
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Delaware, OH 43015
strende@realclearpolitics.com

EDUCATION

Ph.D., The Ohio State University, Political Science, 2023. Dissertation titled *Application of Spatial Analysis to Contemporary Problems in Political Science*, September 2023.

M.A.S. (Master of Applied Statistics), The Ohio State University, 2019.

J.D., Duke University School of Law, *cum laude*, 2001; Duke Law Journal, Research Editor.

M.A., Duke University, *cum laude*, Political Science, 2001. Thesis titled *The Making of an Ideological Court: Application of Non-parametric Scaling Techniques to Explain Supreme Court Voting Patterns from 1900-1941*, June 2001.

B.A., Yale University, with distinction, History and Political Science, 1995.

PROFESSIONAL EXPERIENCE

Law Clerk, Hon. Deanell R. Tacha, U.S. Court of Appeals for the Tenth Circuit, 2001-02.

Associate, Kirkland & Ellis, LLP, Washington, DC, 2002-05.

Associate, Hunton & Williams, LLP, Richmond, Virginia, 2005-09.

Associate, David, Kamp & Frank, P.C., Newport News, Virginia, 2009-10.

Senior Elections Analyst, RealClearPolitics, 2010-present.

Columnist, Center for Politics Crystal Ball, 2014-17.

Visiting Scholar, American Enterprise Institute, 2018-present.

BOOKS AND BOOK CHAPTERS

Larry J. Sabato, ed., *The Red Ripple*, Ch. 15 (2023).

Larry J. Sabato, ed., *A Return to Normalcy?: The 2020 Election that (Almost) Broke America* Ch. 13 (2021).

Larry J. Sabato, ed., *The Blue Wave*, Ch. 14 (2019).

Larry J. Sabato, ed., *Trumped: The 2016 Election that Broke all the Rules* (2017).

Larry J. Sabato, ed., *The Surge:2014's Big GOP Win and What It Means for the Next Presidential Election*, Ch. 12 (2015).

Larry J. Sabato, ed., *Barack Obama and the New America*, Ch. 12 (2013).

Barone, Kraushaar, McCutcheon & Trende, *The Almanac of American Politics* 2014 (2013).

The Lost Majority: Why the Future of Government is up for Grabs – And Who Will Take It (2012).

PREVIOUS EXPERT TESTIMONY AND/OR DEPOSITIONS

Dickson v. Rucho, No. 11-CVS-16896 (N.C. Super. Ct., Wake County) (racial gerrymandering).

Covington v. North Carolina, No. 1:15-CV-00399 (M.D.N.C.) (racial gerrymandering).

NAACP v. McCrory, No. 1:13CV658 (M.D.N.C.) (early voting).

NAACP v. Husted, No. 2:14-cv-404 (S.D. Ohio) (early voting).

Ohio Democratic Party v. Husted, Case 15-cv-01802 (S.D. Ohio) (early voting).

Lee v. Virginia Bd. of Elections, No. 3:15-cv-357 (E.D. Va.) (early voting).

Feldman v. Arizona, No. CV-16-1065-PHX-DLR (D. Ariz.) (absentee voting).

A. Philip Randolph Institute v. Smith, No. 1:18-cv-00357-TSB (S.D. Ohio) (political gerrymandering).

Whitford v. Nichol, No. 15-cv-421-bbc (W.D. Wisc.) (political gerrymandering).

Common Cause v. Rucho, No. 1:16-CV-1026-WO-JEP (M.D.N.C.) (political gerrymandering).

Mecinas v. Hobbs, No. CV-19-05547-PHX-DJH (D. Ariz.) (ballot order effect).

Fair Fight Action v. Raffensperger, No. 1:18-cv-05391-SCJ (N.D. Ga.) (statistical analysis).

Pascua Yaqui Tribe v. Rodriguez, No. 4:20-CV-00432-TUC-JAS (D. Ariz.) (early voting).

Ohio Organizing Collaborative, et al v. Ohio Redistricting Commission, et al, No. 2021-1210 (Ohio) (political gerrymandering).

NCLCV v. Hall, No. 21-CVS-15426 (N.C. Sup. Ct.) (political gerrymandering).

Szeliga v. Lamone, Case No. C-02-CV-21-001816 (Md. Cir. Ct.) (political gerrymandering).

Montana Democratic Party v. Jacobsen, DV-56-2021-451 (Mont. Dist. Ct.) (early voting; ballot collection).

Carter v. Chapman, No. 464 M.D. 2021 (Pa.) (map drawing; amicus).

NAACP v. McMaster, No. 3:21-cv-03302 (D.S.C.) (racial gerrymandering).

Graham v. Adams, No. 22-CI-00047 (Ky. Cir. Ct.) (political gerrymandering).

Harkenrider v. Hochul, No. E2022-0116CV (N.Y. Sup. Ct.) (political gerrymandering).

LULAC v. Abbott, Case No. 3:21-cv-00259 (W.D. Tex.) (racial/political gerrymandering/VRA).

Moore et al., v. Lee, et al., (Tenn. 20th Dist.) (state constitutional compliance).

Agee et al. v. Benson, et al., (W.D. Mich.) (racial gerrymandering/VRA).

Faatz, et al. v. Ashcroft, et al., (Cir. Ct. Mo.) (state constitutional compliance).

Coca, et al. v. City of Dodge City, et al., Case No. 6:22-cv-01274-EFM-RES (D. Kan.) (VRA).

Milligan v. Allen, Case No. 2:21-cv-01530-AMM (N.D. Ala.) (VRA).

Nairne v. Ardoin, NO. 22-178-SDD-SDJ (M.D. La.) (VRA).

Robinson v. Ardoin, NO. 22-211-SDD-SDJ (M.D. La.) (VRA).

Republican Party v. Oliver, No. D-506-CV-2022-00041 (N.M. Cir. Ct. (Lea County)) (political gerrymandering).

Palmer v. Hobbs, Case No. 3:22-CV-5035-RSL (W.D. Wash) (VRA; remedial phase only).

Clarke v. Evers, No. 2023AP001399-OA (Wisc.) (Political gerrymandering; remedial phase only).

Stone v. Allen, No. 2:21-cv-1531-AMM (N.D. Ala.) (VRA).

COURT APPOINTMENTS

Appointed as Voting Rights Act expert by Arizona Independent Redistricting Commission (2020)

Appointed Special Master by the Supreme Court of Virginia to redraw maps for the Virginia House of Delegates, the Senate of Virginia, and for Virginia's delegation to the United States Congress for the 2022 election cycle.

Appointed redistricting expert by the Supreme Court of Belize in Smith v. Perrera, No. 55 of 2019 (one-person-one-vote).

INTERNATIONAL PRESENTATIONS AND EXPERIENCE

Panel Discussion, European External Action Service, Brussels, Belgium, Likely Outcomes of 2012 American Elections.

Selected by U.S. Embassies in Sweden, Spain, and Italy to discuss 2016 and 2018 elections to think tanks and universities in area (declined Italy due to teaching responsibilities).

Selected by EEAS to discuss 2018 elections in private session with European Ambassadors.

TEACHING

American Democracy and Mass Media, Ohio Wesleyan University, Spring 2018.

Introduction to American Politics, The Ohio State University, Autumns 2018, 2019, 2020, Spring 2018.

Political Participation and Voting Behavior, Springs 2020, 2021, 2022, 2023.

Survey Methodology, Fall 2022, Spring 2024.

PUBLICATIONS

James G. Gimpel, Andrew Reeves, & Sean Trende, "Reconsidering Bellwether Locations in U.S. Presidential Elections," Pres. Stud. Q. (2022) (forthcoming, available online at http://doi.org/10.1111/psq.12793).

REAL CLEAR POLITICS COLUMNS

Full archives available at `http://www.realclearpolitics.com/authors/sean_trende/`